Removing barriers to embedded generation:

a fine-grained load model to support low voltage network performance analysis

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Removing barriers to embedded generation: a fine-grained load model to support low voltage network performance analysis

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A thesis submitted in partial fulfilment of the requirements of De Montfort University for the degree of Doctor of Philosophy

January 2005

Institute of Energy and Sustainable Development
De Montfort University, Leicester

A Glass of Wine

by Andrew Motion

Exactly as the setting sun
clips the heel of the garden,

exactly as a pigeon
roosting tries to sing
and ends up moaning,

exactly as the ping
of someone's automatic carlock
dies into a flock
of tiny echo-aftershocks,

a shapely hand of cloud
emerges from the crowd
of airy nothings that the wind allowed
to tumble over us all day
and points the way

towards its own decay
but not before
a final sunlight-shudder pours
away across our garden-floor

so steadily, so slow
it shows you everything you need to know
about this glass I'm holding out to you,

its open eye
enough to bear the whole weight of the sky.

Abstract

The objective of this thesis is to create a model, which provides a detailed description of the electrical load on a low voltage distribution network in the context of a typical UK urban feeder from a primary transformer. The aim of the work, when used in association with a power flow analysis package, is to help to provide a risk assessment for over-voltage events and over-heating in the network when different levels of embedded generation are applied.

A fine-grained domestic load model has been constructed with a three layered approach to provide per-consumer, 1-minute averaged loads on an end-use basis. Datasets from the Load Research Group have been used as the starting point and form the basis for layer 1 which represents group-averaged demands on a half-hourly basis. Layer 2 of the model introduces diversity in terms of number of occupants, living space, ownership and socio-economic factors. Layer 3 uses appliance duty cycles to create wider variations by random triggering to derive 1-minute loads from assigned half-hourly values. The domestic model has been adapted for use with smaller (sub 100kW) non-domestic consumers.

The research question for this study is whether or not the models provide an adequate representation of the electricity demand for a typical urban LV network, judged in terms of a variety of parameters. The output from the domestic model compares well with measured data giving realistic demand characteristics in terms of mean, peak, load factor and distribution. Compared against diversified peak demands currently in use within the industry, the model estimates values within 10% for groups fewer than 25 and 5% for groups of 100 or more.

When used together with a power flow analysis package, the predicted voltage variation agrees with measured results in terms of mean value and distribution. The investigation of time and group averaging of demand, power factor surveys and, with a matching model for PV and solar thermal output, studies into electrical demand reduction within mixed communities are all possible additional applications for the model.

Acknowledgements

This research was carried out at the Institute of Energy and Sustainable Development, De Montfort University, Leicester, England. It was funded by the Engineering and Physical Sciences Research Council, project number GR/N35694/01.

I should like to express my gratitude to Professor Kevin Lomas for giving me the opportunity to conduct this research. I am indebted to my supervisor Dr. Mark Rylatt for his constant encouragement and support and to Dr. John Mardaljevic for providing additional material and viewpoints. Dr. Murray Thomson and Professor David Infield at CREST, Loughborough University have also offered much needed support in terms of the electrical focus for the work.

Many individuals have helped along the way by freely providing background material, including Dougal McQueen at CREST, David Cooper of the Load Research Group, François Nortjé of Inspired Interfaces, Professor Ron Herman, Professor Robert Bartels, Drs. Patrick and Hannah Devine Wright. Steven Firth and Graeme Stuart generously provided additional datasets for validation. I am most grateful to the contacts at the UK's Distribution Network Operators who completed the User Needs Questionnaire and voiced their opinions bringing a practical aspect to the research.

Finally I should like to thank my husband, Phil, and children, Liz and Chas, who have endured the ups and downs of academic research without complaint.

This work is dedicated to my aunt Deborah Winterford who is a perfect role model in having the determination to keep going no matter how hard it gets.

I declare that the content of the submission represents solely my own work.

Melody Stokes, December, 2004

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GLOSSARY

Abbreviations

ADMD	After Diversity Maximum Demand (peak in group demand)
ANNSTLF	Artifical Neural Network Short Term Load Forecaster
ASC	Authorised Supply Capacity
BREHOMES	Building Research Establishment Housing Models for Energy Studies
BST	British Summer Time
CHP	Combined Heat and Power
DASH	Direct Acting Space Heating
DEFRA	Department of the Environment, Farming and Rural Affairs
DF	Diversity Factor (ratio of group peak in demand per consumer)
DNO	Distribution Network Operator
DREAM	Dynamic Regional Energy Analysis Model
DSM	Demand Side Management
DTI	Department of Trade and Industry
E7	Economy 7 (2 stage tariff for on and off peak demands)
EU	European Union
GIS	Geographical Information System
GMT	Greenwich Mean Time
HV	High Voltage
LRG	Load Research Group (originally, part of Electricty Association)
LV	Low Voltage
MD	Maximum Demand
MDI	Maximum Demand Indicator
MTP	Market Transformation Programme
MV	Medium Voltage
NBDS	Non-Domestic Building Database Survey
NDEEM	Non-Domestic buildings Energy and Emissions Model
PF	Power Factor
PV	Photovoltaic
RET	Renewable Energy Technologies
SAP	Standard Assessment Rating
SEnTIENT	Solar Energy Technology: Impact on Electricity Networks Tool
SIC	Standard Industrial Classification of economic activities
UN	United Nations
UK	United Kingdom
UR	Un-Restricted (single rate tariff)
VO	Valuation Office

Symbols

(Note: the symbols that are used in equations from other sources have been retained. When two separate meanings are assigned to the same symbol, the relevant meaning is made clear in the accompanying text)

a	product of ADMD and DF (kW/consumer)
a_1, a_2, a_3	constant values for Duffie and Beckman equation
A	constant value for Boltzmann's statistical analysis of clearness index
A_1	theoretical area required for solar panel (m^2)
A_2	actual panel area (m^2)
A_{array}	area PV panel array
$A_{thermal}$	panel area required to heat 40 litres of water during June (m^2)
b_1, b_2, b_3	constant values for Duffie and Beckman equation
B	calculated non-dimensional parameter for solar thermal panel
d	loss and diversity allowance (kW)
d_{heat_max}	maximum threshold for underlying trend in heating demand
d_{heat_min}	minimum threshold for underlying trend in heating demand
d_{heat_sine}	underlying sinusoidal trend for heating demand in given half-hour
d_{lights_max}	maximum threshold for underlying trend in lighting demand
d_{lights_min}	minimum threshold for underlying trend in lighting demand
d_{lights_sine1}	1st underlying sinusoidal trend for lighting demand in half-hour
d_{lights_sine2}	2nd underlying sinusoidal trend for lighting demand in half-hour
$d_{HH\_group\_cook}$	normalised, half-hourly, group averaged demand - cooking
$d_{HH\_group\_ff}$	normalised, half-hourly, group averaged demand – fridge-freezer
$d_{HH\_group\_fridge}$	normalised, half-hourly, group averaged demand – refrigerator
$d_{HH\_group\_freezer}$	normalised, half-hourly group averaged demand - freezer
$d_{HH\_group\_heat}$	normalised, half-hourly group averaged demand - heating
$d_{HH\_group\_misc}$	normalised, half-hourly, group averaged miscellaneous demand
$d_{HH\_group\_water}$	normlaised, half-hourly, group averaged demand – water heating
$d_{HH\_group\_wet}$	normalised, half-hourly, group averaged demand – washing
D	modelled demand for any end-use, model Layer 1
D_{active_n}	active component of the demand for nth end-use (kW)
$D_{HHappliance\_n}$	typical half-hourly demand during an appliance event (kW)
$D_{HH\_group\_cook}$	half-hourly group averaged demand for cooking (kW)
$D_{HH\_group\_ff}$	half-hourly group averaged demand for fridge-freezer (kW)
$D_{HH\_group\_freezer}$	half-hourly group averaged demand for freezer (kW)
$D_{HH\_group\_fridge}$	half-hourly group averaged demand for refrigerator (kW)
$D_{HHgroup\_heat}$	half-hourly group averaged demand for heating (kW)
$D_{HH\_group\_lights}$	half-hourly group averaged demand for lighting (kW)
$D_{HHgroup\_misc}$	half-hourly group averaged demand for miscellaneous items (kW)
$D_{HHgroup\_n}$	annual set of modelled half-hourly group demands, nth end-use (kW)
$D_{HHgroup\_water}$	half-hourly group averaged demand for water heating (kW)
$D_{HHgroup\_wet}$	half-hourly group averaged demand for washing (kW)
$D_{HHspecific\_n}$	half-hourly assigned demand for nth end-use (kW)

$D_{\text{HHspecific\_cook}}$	half-hourly assigned demand for cooking appliances(kW)
$D_{\text{HHspecific\_fridge}}$	half-hourly assigned demand for refrigeration appliances(kW)
$D_{\text{HHspecific\_heat}}$	half-hourly assigned demand for space heating (kW)
$D_{\text{HHspecific\_lights}}$	half-hourly assigned demand for lighting(kW)
$D_{\text{HHspecific\_misc}}$	half-hourly assigned demand for miscellaneous appliances(kW)
$D_{\text{HHspecific\_water}}$	half-hourly assigned demand for water heating (kW)
$D_{\text{HHspecific\_wet}}$	half-hourly assigned demand for washing appliances(kW)
D_{max}	maximum end-use demand in underlying trend, model Layer 1
$D_{\text{max\_n}}$	annual peak demand for the nth end-use (kW, from LRG data)
$D_{\text{max\_trend\_n}}$	annual demand peak for nth end-use (kW)
D_{min}	minimum end-use demand in underlying trend, model Layer 1
$D_{\text{min\_n}}$	1-minute demand for the nth end-use (kW)
$D_{\text{min\_appliance\_n}}$	1-minute demand during an appliance event for the nth end-use (kW)
$D_{\text{measured\_n}}$	half-hourly averaged dataset (kW, LRG measured data)
$D_{\text{model\_n}}$	demand dataset for the nth end-use used for the model (kW)
D_n	set of modelled annual patterns for half-hourly demand, nth end-use
$D_{\text{reactive\_n}}$	reactive component of demand for nth end-use (kW)
D_{sine}	sinusoidal end-use trend in underlying trend, model Layer 1
D_{total}	total load (kVA)
$D_{\text{\_total\_active}}$	matrix of total active loads (kW)
$D_{\text{\_total\_reactive}}$	matrix of total reactive loads (kVAR)
E_{eg}	hourly global irradiance on a horizontal surface (W/m^2)
$E_{\text{eg\_min}}$	1-minute global irradiance on a horizontal surface (W/m^2)
$E_{\text{eg\_min\_tilt}}$	1-minute global irradaicne on a tilted surface (W/m^2)
$E_{\text{eg\_tilt}}$	hourly global irradiance on a tilited surface (W/m^2)
E_{ET}	hourly extraterrestrial irradiance (W/m^2)
E_k	annual cooking fuel used (GJ/year)
F	calculated non-dimensional parameter for solar thermal panel
G_0	solar constant (1367 W/m^2)
G_{tilt}	annual mean of daily peak irradiation (W/m^2)
H_{min}	1-minute averaged solar power falling on panel (kW)
H_{tilt}	annual mean value for daily mean irradiation (MJ/m^2) on tilted surface
i	integer variable, denoting day number (1 - 365/366)
j	integer variable, denoting half-hour reference number (1 - 48)
k	constant
	integer designating the 1-minute reference during a day
k_1, k_2	empirical constants (for Verlander's equation)
$k_{\text{cook\_HH}}$	sine constant for half-hourly demand, cooking
$k_{\text{ff\_HH}}$	sine constant for half-hourly demand, fridge-freezer
$k_{\text{freezer\_HH}}$	sine constant for half-hourly demand, freezer
$k_{\text{heat\_HH}}$	sine constant for half-hourly demand, heating
$k_{\text{lights\_HH}}$	sine constant for half-hourly demand, lighting
$k_{\text{misc\_HH}}$	sine constant for half-hourly demand, miscellaneous
$k_{\text{water\_HH}}$	sine constant for half-hourly demand, water heating
$k_{\text{wet\_HH}}$	sine constant for half-hourly demand, washing appliances
$k_{\text{own\_n}}$	factor designating ownership (value either 0 or 1)
$k_{\text{own\_cook}}$	factor designating ownership of cooking appliances
$k_{\text{own\_fridge}}$	factor designating ownership of refrigeration appliances
$k_{\text{own\_heat}}$	factor designating ownership of space heating

k_{own_water}	factor designating ownership of water heating
k_{own_wet}	factor designating ownership of washing appliances
k_{occ_n}	scaling factor depending on number of occupants
k_{occ_cook}	occupant scaling factor for cooking demand
k_{occ_fridge}	occupant scaling factor for refrigeration demand
k_{occ_heat}	floor area scaling factor for space heating demand
$k_{occ\_lights}(i,j)$	occupant scaling factor for lighting demand
k_{occ_water}	occupant scaling factor for water heating demand
k_{occ_wet}	occupant scaling factor for washing demand
k_{econ_n}	scaling factor depending on income or lifestyle indicator
$k_{lifestyle\_wet}$	lifestyle scaling factor for washing demand
$k_{lifestyle\_lights}$	lifestyle scaling factor for lighting demand
k_{income_lights}	income scaling factor for lighting demand
$k_{hi\_lo\_water}$	scaling factor for variations in water heating demand
k_t	1-minte averaged clearness index
k_{t0}	mean value 1-minute averaged clearness index during given hour
k_{TH}	hourly averaged clearness index
k_{T_min}	1-minute clearness index
K	collector performance parameter
L	total load for group (in calculation for ADMD, kW)
L_{water}	daily energy demand for water heating (MJ)
m_{fridge_HH}	half-hourly scaling factor for refrigerators (group average)
M	solar thermal collector sizing parameter (ratio energy available to energy required)
n	integer signifying end-use equivalent number of days between BST/GMT or vice versa
N	number of consumers (over a defined area of the network) number of occupants (per dwelling)
N_d	day number in a given year
N_y	total number of days in a given year
p_{cook}	estimated annual peak diversified demand for cooking (kW)
p_{ff}	estimated annual peak diversified demand for fridge-freezer (kW)
$p_{freezer}$	estimated annual peak diversified demand for freezer (kW)
p_{fridge}	estimated annual peak diversified demand for refrigerator (kW)
p_{lights}	estimated annual peak diversified demand for lighting (kW)
p_{misc}	estimated annual peak diversified demand for miscellaneous (kW)
p_{water}	estimated annual peak diversified demand for water heating (kW)
p_{wet}	estimated annual peak diversified demand for washing (kW)
P	active load (kW) peak demand/consumer (in Verlander's equation, kW)
PF	power factor
PF_n	power factor for the nth end-use
Pr	probability of an event occurring
PV_{hourly}	hourly averaged PV output (kW)
PV_{min}	1-minute averaged PV output (kW)
Q	reactive load (kW)
Q_{annual}	total annual solar energy supplied to hot water system (MJ)

Q_{min}	solar energy supplied to hot water system in a given minute (MJ)
r	random number from a normal distribution
r_{cook_HH}	random number from a normal distribution for cooking demand
r_{ff_HH}	random number from normal distribution for fridge-freezer demand
r_{fridge_HH}	random number from normal distribution for refrigerator demand
$r_{freezer\_HH}$	random number from normal distribution for freezer demand
$r_{lights\_max\_HH}$	random number from normal distribution for maximum lighting demand
$r_{lights\_min\_HH}$	random number from normal distribution for minimum lighting demand
$r_{lights\_sine\_HH}$	random number from normal distribution for sinusoidal lighting demand
r_{max}	random number associated with maximum threshold demand
r_{min}	random number associated with minimum threshold demand
r_{misc_HH}	random number from normal distribution for miscellaneous demand
r_{heat_HH}	random number from normal distribution for heating demand
r_{water_HH}	random number from normal distribution for water heating demand
r_{wet_HH}	random number from normal distribution for washing demand
R	linearly generated random number (value 0 to 1, inclusive) storage parameter associated with solar thermal water heating
R_b	ratio of beam irradiation on tilted surface to that on the horizontal
s	sine amplitude
$s_{1\_lights\_HH}$	1st sine amplitude factor for given half-hour, lighting demand
$s_{2\_lights\_HH}$	2nd sine amplitude factor for given half-hour, lighting demand
s_{cook_HH}	sine amplitude factor for given half-hour, cooking demand
s_{ff_HH}	sine amplitude factor for given half-hour, fridge-freezer demand
$s_{freezer\_HH}$	sine amplitude factor for given half-hour, freezer demand
s_{heat_HH}	sine amplitude factor for given half-hour, heating demand
s_{misc_HH}	sine amplitude factor for given half-hour, miscellaneous demand
s_{water_HH}	sine amplitude factor for given half-hour, water heating demand
s_{wet_HH}	sine amplitude factor for given half-hour, washing appliance demand
t	time (based on 24 hour clock)
T	total load (i.e. real and reactive, kW)
T_{air}	mean daytime air temperature (°C)
T_{cold}	temperature of incoming water supply (°C)
TFA	total floor area (m²)
T_{hot}	desired hot water temperature (°C)
T_{ref}	reference cell termperature at standard test conditions for PV panel (°C)
P	peak demand per consumer (kW) – Verlander's equation
Pr	probability

U	collector heat loss coefficicient (W/m^2K)
V_s	storage volume required for solar thermal heated water (litres)
V_{water}	estimated daily hot water demand (litres)
W	annual energy consumption (Verlander's equation, MWh)
Z_i	empirical adjustment in variation for position of sun, per hour
β	angle of inclination for tilted surface (degrees)
δ	vertical angle of sun due to annual trend (degrees)
η_i	hourly value for array efficiency
η_{mp_ref}	maximum power point efficiency of PV panel (%)
η_o	zero loss collector efficiency
η_e	efficicency of power conditioning equipment (%)
λ	calculated non-dimensional parameter for solar thermal panel constant value for Boltzmann's statistical analysis of clearness index
μ_{mp}	temperature coefficient of PV panel (V/°C)
ρ	reflectance coefficient
φ	sine phase latitude (in degrees)
φ_{cook_HH}	sine phase angle for half-hourly demand, cooking (radians)
φ_{ff_HH}	sine phase angle for half-hourly demand, fridge-freezer (radians)
φ_{heat_HH}	sine phase angle for half-hourly heating demand (radians)
$\varphi_{1\_lights\_HH}$	1st sine phase angle for half-hourly lighting demand (radians)
$\varphi_{2\_lights\_HH}$	2nd sine phase angle for half-hourly lighting demand (radians)
φ_{misc_HH}	sine phase angle for half-hourly miscellaneous demand (radians)
φ_{total}	phase angle (between total load vector, T, and real load, P)
φ_{water_HH}	sine phase angle for half-hourly water heating demand (radians)
φ_{wet_HH}	sine phase angle for half-hourly washing demand (radians)
σ_{cook}	standard deviation for random component, cooking demand
σ_{ff}	standard deviation for random component, fridge-freezer demand
$\sigma_{freezer}$	standard deviation for random component, freezer demand
σ_{heat}	standard deviation for random component, heating demand
σ_{lights_min}	standard deviation for random component, minimum lighting demand
σ_{lights_max}	standard deviation for random component, maximum lighting demand
σ_{lights_sine}	standard deviation for random component, sinusoidal lighting demand
σ_{misc}	standard deviation for random component, miscellaneous demand
σ_{water}	standard deviation for random component, water heating demand
σ_{wet}	standard deviation for random component, washing demand
σ_{max}	standard deviation for random component (maximum demand)
σ_{min}	standard deviation for random component (minimum demand)
σ_{sine}	standard deviation for sinusoidal demand trend
$\tau\alpha/UL$	heat transfer rate for PV panel (m^2 K/W)
ω	vertical angle of sun due to daily cycle (degrees)

Chapter

1 Introduction

'When you drink from the stream remember the spring.'

CHINESE PROVERB

On the 14th August, 2003, the lights went out in New York. Commuters were stranded in the city overnight; millions were without power from Michigan to Massachusetts. A few weeks later, two significant outages in the UK caused chaos in London's rush hour and halted manufacture in the Midlands. During September, similar problems hit Scandinavia and Italy. In all, over 112 million people were affected. The investigations that followed revealed various communication and technical breakdowns, unusually in the case of the UK (Figure 1-1) implicating problems in the low voltage (LV) networks [Bialek, 2003]. The blackouts of 2003 served to focus public attention on the rapidly increasing electrical demands made on potentially fragile distribution networks and our total dependence on a secure supply. The decreasing margins of safety between supply and demand caused wide scale debate. In order to operate within the constraints of the existing infrastructure, distribution network operators (DNOs) were further incentivised to manage demand and to control how the load was distributed over the networks.

Energy demand reduction together with the use of renewable sources was already on the agenda for many governments around the World as a result of the Kyoto Protocol [UN, 1997]. Climate change had been linked with the increased emissions of the five 'greenhouse' gases, notably carbon dioxide for which atmospheric levels have rapidly increased over the last century as we burn more and more fossil fuels

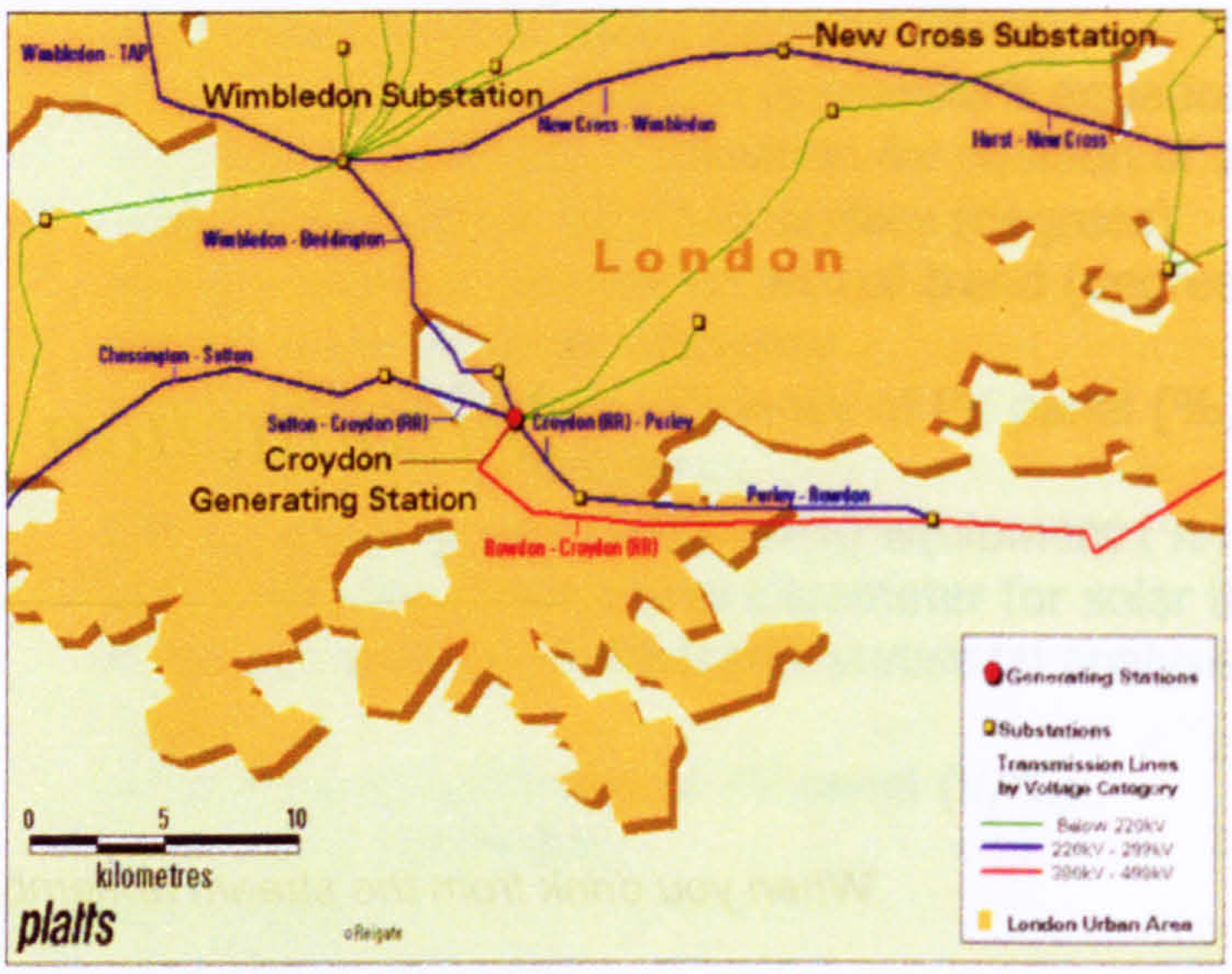

Figure 1-1: Map showing the area and networks affected in the London power outage of 2003 [Platts, 2004] - used with permission from platts.com, a website of Platts

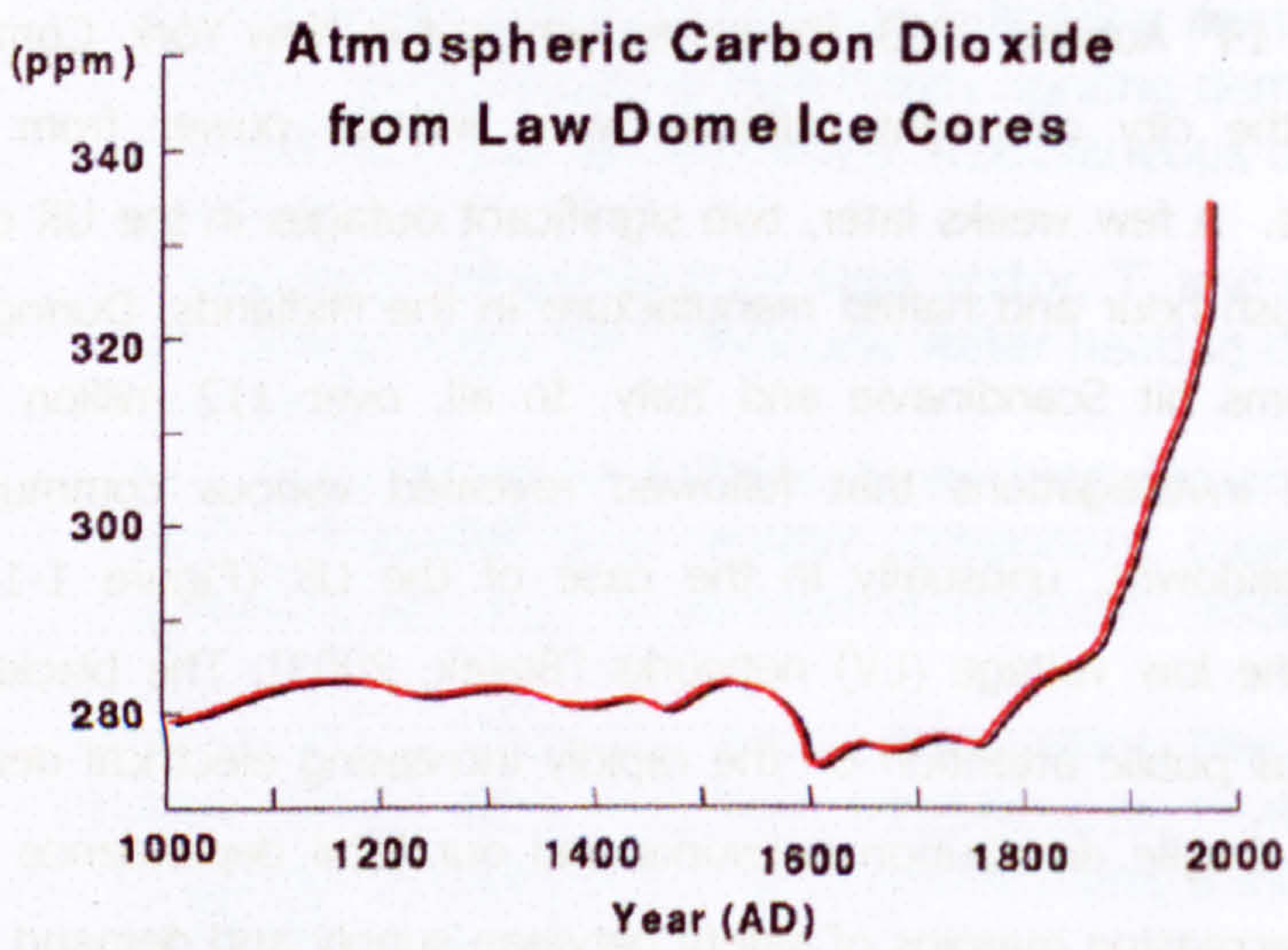

Figure1-2: Variations in carbon dioxide levels found in ice core sample from Antarctica [Etheridge, 1996]

to sustain our lifestyles (Figure 1-2). The Kyoto Protocol established national targets designed to roll back levels to 5% below the 1990 baseline by 2012. Following ratification by 30 industrialised partners of the United Nations (with the notable exception of the USA), the Protocol becomes legally binding in February, 2005. Within Europe, the European Community (EC) has embraced the intentions and placed a high priority on increasing the production of electricity by renewable means

[EC, 2001] with a target to achieve 22% by 2010. Individual member countries have national targets, with a level of 10% for the United Kingdom (UK), controversially included in a recent Energy White paper [DTI, 2003a] as an objective rather than a firm target.

Both the UN Earth Summits and the UK Government acknowledge that involvement in renewable energy has to be at a community level to be successful. Some local authorities have chosen to set themselves some radical targets, notably the city of Leicester, aiming for 20% generation from renewables by 2020 [Leicester City Council, 2002]. Within urban environments the most suitable forms of new and renewable energy technologies (RETs) are photovoltaic, solar thermal and combined heat and power (CHP) plants. Thus the UK's electricity industry is increasingly required to embrace small scale distributed generation and to manage the loading of a network that was originally designed some seventy years ago on the basis of outward flow from centralised generators. Since the solar RETs are weather dependent, supply levels are likely to be much more dynamic. A far more detailed understanding of the distributed demand is required on a finer time interval in order to research the localised effects of distributed generation.

Even if uptake of RETs fails to achieve desired levels, high concentrations within urban communities could potentially cause problems in the LV networks [Lees et al, 2003]. In November, 2001, the Distributed Generation Co-ordinating Group was established jointly by the Department of Trade and Industry and Ofgem, UK's energy regulating body. This group continues to investigate the economic and technical challenges of distributed generation. The DNOs are key participants in this group – not least because much of their revenue is derived from the power flowing through the LV networks.

When installing or creating new network designs, voltage drops and outages are key concerns to reduce operating costs. The first transmission and distribution grids were built in the UK, locally in the 1920s and further developed at a national level in the late 1940s. With responsibility for the lower voltage end of the network (sub 132kV), the DNOs have tended to operate reactively – extending networks as required by new developments or troubleshooting power quality issues. Under pressure to cut costs and maintain the quality of supply, DNOs are seeking to operate actively with more sophisticated designs to improve the performance of their networks.

Although design tools have improved, some allowing visualisation of the network on a Geographical Information System (GIS), the methods of representing the network loading have remained relatively constant over the years. Whilst refined models of demand have been developed for the high and medium voltage transmission networks, generally for planning and trading purposes, simple estimates of peak and average demands[1] of consumers have traditionally been used for the LV circuits. Whereas at higher voltages, the diversity of demand tends to smooth the daily and annual profiles, the loading of the LV networks has to take account of the spiky nature of the individual demands and is thus more difficult to predict and model (Figure 1-3). Whilst some elements of the demand (e.g. lighting during hours of darkness) are less diversified, others (e.g. use of kettles or hobs) can be very different from one consumer to another.

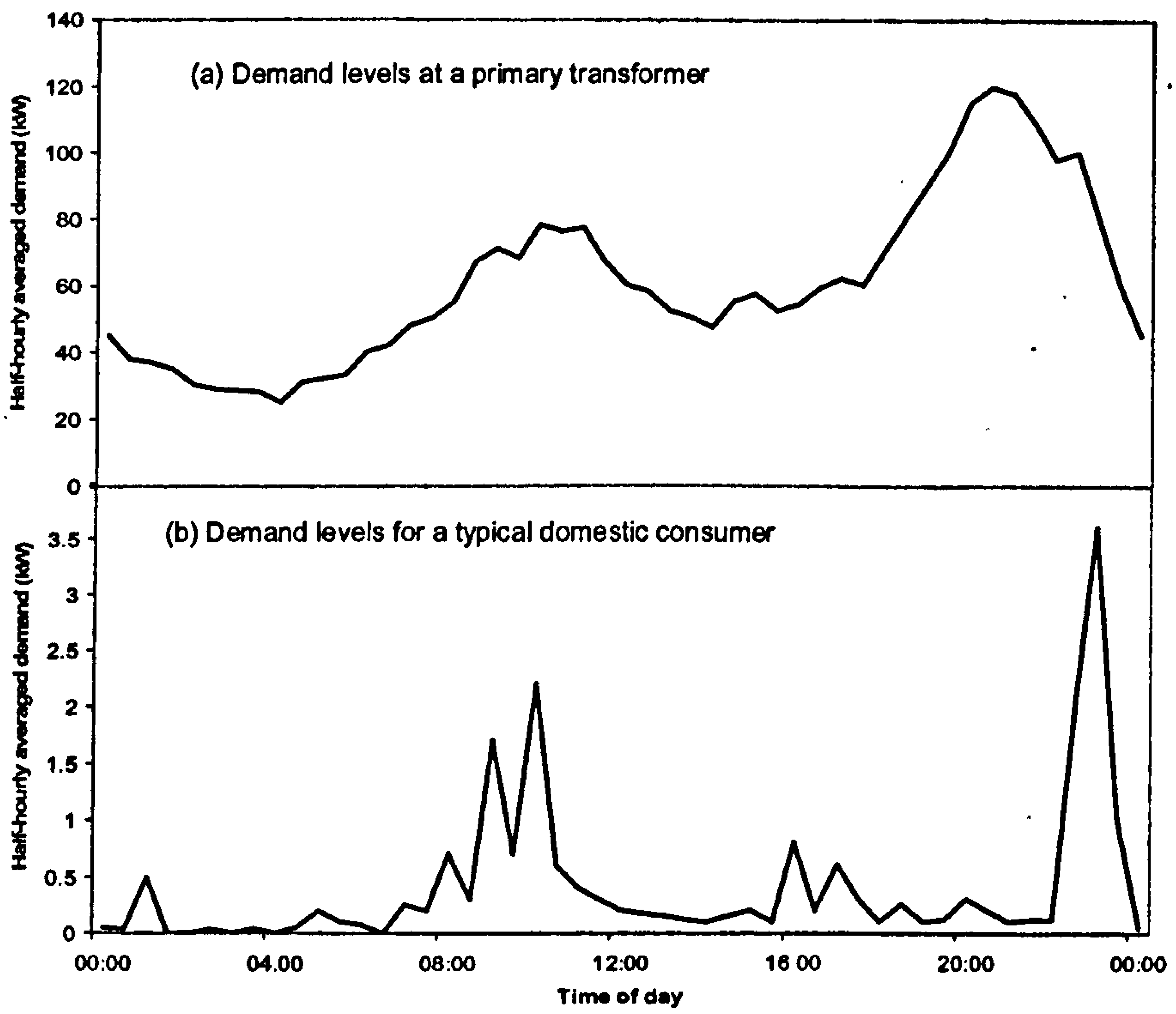

Figure 1-3: Typical daily profile for (a) demand at a primary transformer and (b) for an individual domestic consumer

[1] Throughout this document the terms 'load' and 'demand' are used synonymously. Both are considered to refer to the electrical power (units kW). On occasions 'demand' is used in the context 'energy demand' (units kWh) which refers to energy consumption.

Electrical demand is also comprised of active (real) and reactive (imaginary) elements which depend on the nature of the load (Figure 1-4). The total load is the vector sum of the two components (typically the ratio of the active to the total load is around 0.96). Although small, the reactive component increases the current flowing (affecting the resistive heat losses, with impacts on power quality) and has to be accounted for during design and operation of the networks. Consequently, there is value in understanding not only the way in which the load changes spatially and temporally over the LV network but also the nature of the demand in terms of appliances and end-use.

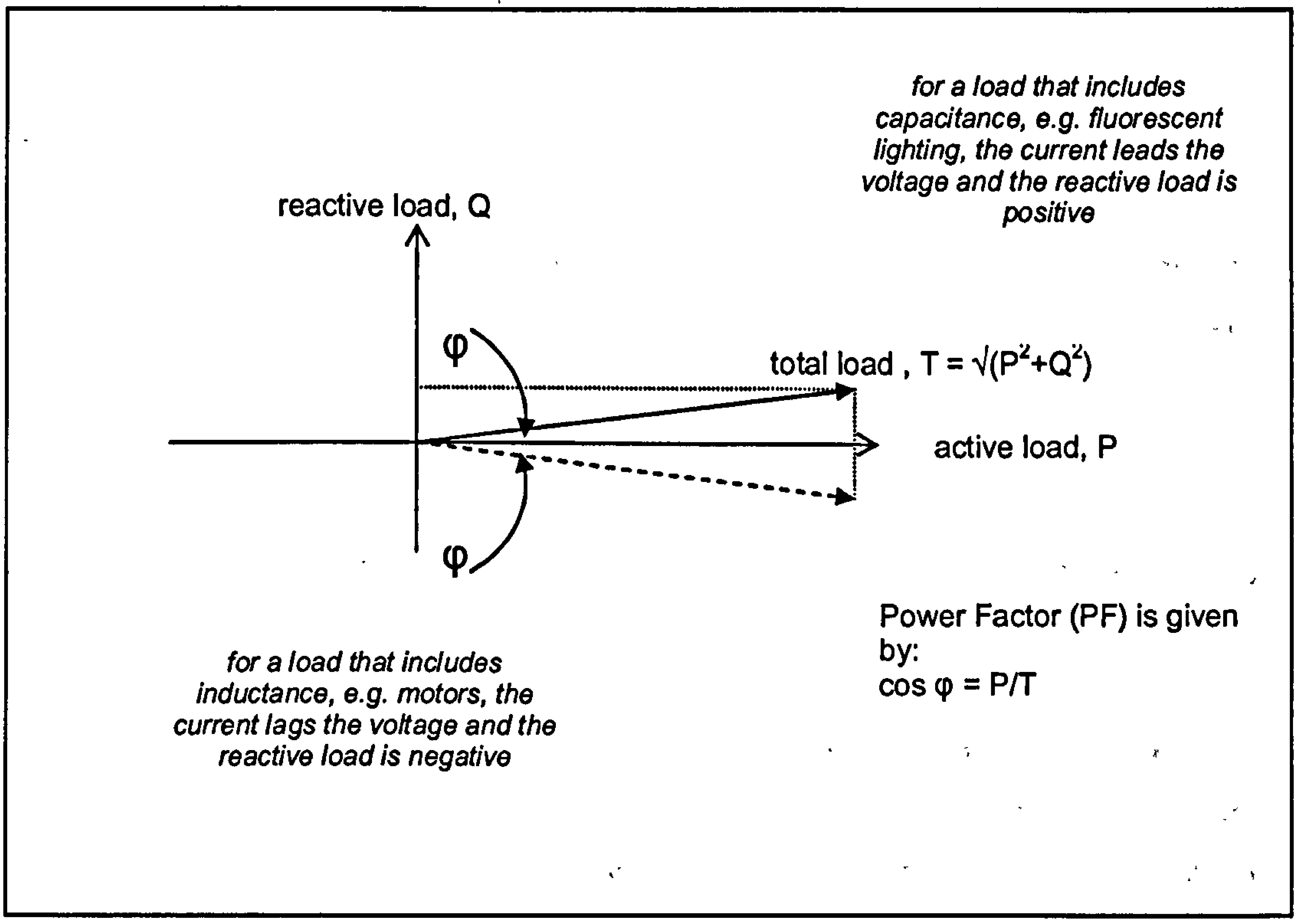

Figure 1-4: Explanation of the relationship between the total load and the active and reactive components

As well as the DNOs, energy researchers are interested in quantifying and qualifying consumer electricity usage in order to develop strategies for demand reduction and implementation of RETs. Such research can be hampered by the difficulties of obtaining data for electrical demand [Boardman et al, 1994; Bass, 1997]. Since the UK electricity industry was privatised, trading between generators, transmitters, distributors and suppliers has been on the basis of half-hourly demand, one month in advance. Although larger consumers (over 100 kW peak demand) are metered half-hourly, smaller consumers are monitored for billing purposes on a monthly or quarterly basis. Consequently, there has been a need to develop demand profiles for trading proposes and these have been based on samples of half-hourly data monitored by the Load Research Group (LRG) of the Electricity Association [EA, 1998][2]. The profiles and data, accessible to members of the LRG, have not been publicly available. Whilst in Canada and the USA, such data is often provided at little or no cost, on an hourly basis by consumer type for a variety of locations [e.g. MAISY, 2004], such datasets are elusive in the UK.

The research described in this thesis has therefore attempted to provide a set of models that supply the synthesised loading on a typical urban LV network. The research was originally conducted as part of the wider project, Solar City, funded by the Engineering and Physical Sciences Research Council (EPSRC) [Stokes et al, 2002]. The overall objective of the project was to produce a GIS-based software package to calculate the impact of solar energy technologies, principally solar PV, on the LV system. Key objectives were these:

- the calculation of electrical loads at an appropriate time scale together with the corresponding PV output
- the prediction of voltage rise and line losses within a real urban supply network

The tool is intended to support decisions concerning the technical and economic impacts of solar RETs on electrical demand and the local supply network. The load models have been designed to receive inputs from the main module of the Solar City tool that describes the consumer at each connection point (e.g. whether domestic or non-domestic, floor area). The output is fed to a load flow analysis package [Thomson et al, 2003] for testing the network performance. Although the models of electricity demand described in this thesis have been developed in close collaboration with the other elements of this application, they do not relate exclusively to this package.

[2] The Electricity Association was disbanded in September, 2004. The responsibility for generating profiles for settlement purposes has transferred to Elexon [Elexon, 2004(a)].

The specific objective for the load models was therefore to synthesise a per consumer description of the point electrical loading at each connection node on a typical urban LV network, during dates selected by the user and on a suitably fine timescale that captures the varying nature of the demand. A complete description of the load was required for the power flow analysis, i.e. both active and reactive components in order to examine the total current flowing in the network. The emphasis for the work has principally been the electrical demands of domestic consumers together with smaller non-domestic consumers, such as offices and shops, as might be found in inner city locations. The models aim to provide the distributed load prior to the application of solar panels that create an exported load or reduced demand, in the case of solar thermal (complementary models for this aspect are described in Appendix G).

The realism of the network loading and success of the outcome can be judged in many ways. The scale and pattern of demand for individual consumers as well as the diversity of demand within a group, such as those connected to a single feeder of a primary transformer, are all important components of the load description. Such realism may be quantified by investigating the following for both individual consumers and for the group aggregate:

- peak demands
- mean demands and total energy consumption over the selected period
- load factor (being the relationship between the mean and peak values)
- the general shape of demands on an averaged or daily basis
- the distribution of demands over the given period

The work did not set out to provide highly accurate predictions of peak or mean demand within the LV network (such as the Tesla model [Tesla, 2000], described further in Chapter 2, which aims to provide values with less than 2% accuracy) nor exact patterns of demand for a given consumer or group of consumers (such as the ESP-r tool, also described further in Chapter 2, which builds a highly detailed simulation for building design analysis). Instead, the aim of the load models was to provide realism in the sense of demand values and characteristics, judged both individually and as a group, that were within a typical range when compared to measured values investigated by other researchers (for example Newborough and Augood's study of 30 dwellings [Newborough and Augood, 1999]) and commonly used by DNOs for network design and operation.

The models described have been based on the half-hourly measurements made by the LRG, provided as averages for a group of homes across the UK, for a variety of appliances and end-uses. They have been designed and developed to fulfil the following specification:

- Realistic description (as judged by the criteria mentioned earlier) of the network loading in terms of distribution, diversity, time-variation and scale, for both active and reactive components
- Clear practical basis with a methodological approach to allow users to modify and adapt the underlying parameters or to add new end-uses
- Modular approach with identifiable objects and associations to facilitate use with software tools, such as GIS and existing network design tools, yet small enough to run on a typical personal computer.
- Fine-granularity with a time interval for load averaging that matches the changes in RET supply (generally considered to be 1-minute – discussed further in chapter 2) and spatially to represent adequately the load distribution on an urban LV network (i.e. per consumer connection)
- Suitability for mixed inner-city communities, covering domestic and light non-domestic
- Public availability of the models and methodology (whilst respecting the commercial sensitivity of the original data).

Thus the models seek to fill a gap by providing simulations of electricity demand. The novelty of the models lies in the combination of fine-granularity, an end-use approach, synthesised diversity and their extension to non-domestic consumers. This is demonstrated further in Chapter 2 (Figure 1-5), which digs deeper into some of the difficulties surrounding load modelling and describes the various techniques used by others to overcome them.

The models are broadly based on a three layer concept, described in outline in Chapter 3. The first layer, detailed in Chapter 4, provides a representation of the half-hourly demand for a group of domestic consumers. The second layer, covered by Chapter 5, introduces various elements of diversity to make specific assignments to individual consumers. The third layer synthesises 1-minute averaged demands from the half-hourly assignment and is described further in Chapter 6. The basic structure of the domestic model may be applied broadly to non-domestic consumers and the proposed approach is discussed further in Chapter 7.

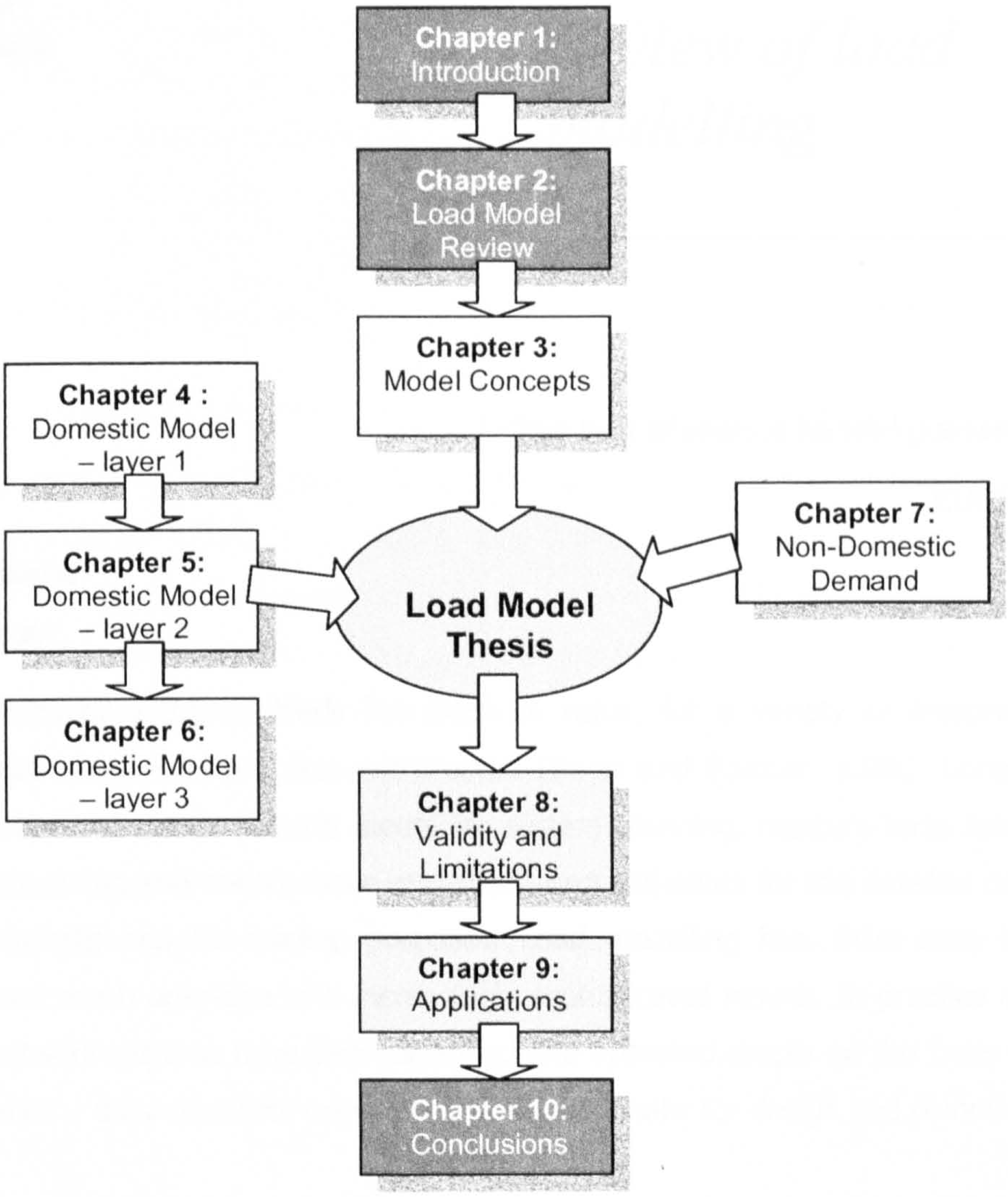

Figure 1-5: Schematic outline of thesis structure showing chapter content

Chapter 8 investigates how the models, operating at all three layers, compare with a variety of measured data and identifies some of the limitations. Chapter 9 looks in more detail at the Solar City project and how the models are intended to be used, together with ways in which they may be adapted for other applications. Finally, Chapter 10 reflects on the novelty of the work and reviews the key findings of this study.

Chapter

2

Review of load modelling

'The best of seers is he who guesses well.'

EURIPEDES

Forecasting electrical loads has been of value, for a variety of reasons, since national networks were first constructed [Bunn and Farmer, 1985]. Longer-term predictions of trends provide inputs for system planning, medium term forecasting for scheduling and maintenance and short-term estimates for the detailed operation of networks and for trading purposes. Load modelling has, from time to time, received much attention with increasingly sophisticated results. In practice many of the network systems have been designed and operated simply on the basis of peak demands – daily peaks for operation and annual peaks for design and planning.

For network designers and operators, a key task is to manage the voltage drops across the transformers and connectors to achieve a reliable supply within regulated voltage bands at lowest possible cost. This balancing act requires an understanding of two elements – the basic design of the network (the resistance and reactance of the network components affect voltage drop) and the loading that arises from the consumer demand (since the voltage drop also depends on the current flowing). This chapter continues by looking at each of these strands in turn.

Thereafter, the path of load model development is traced from simple application of spot values through to more refined techniques that provide a continuously varying pattern of demand. Valuable work has already been undertaken into modelling energy consumption based on appliances and end-uses. Some of these models will be described, as the concepts are important for this thesis. On a more practical note, the application of load models is set in context: there are many different tools now used by the UK energy industries and some of the ways in which loads are defined within these tools will be described. Finally, the various methods and models are reviewed, compared and contrasted to establish how they measure against the requirements, as described in chapter 1.

2.1 The Network

2.1.1 Outline of the UK Electricity System

The UK electricity industry is split for trading purposes into four distinct areas – generation, transmission, distribution and supply. Centralised generators feed electrical energy into the transmission networks (National Grid), with a voltage reduction from 400 kV to 33kV for wider distribution. Primary transformers drop the voltage further to 11kV (Figure 2-1). In the city of Leicester (population of around 300,000) for example, there are approximately 25 primary sub-stations. Within the LV network, voltage is reduced again in the distribution transformers to a 400V 3-phase (230V single phase) supply. In the Braunstone area of Leicester (population around 15,000) for example, there are approximately 150 distribution sub-stations.

A typical arrangement for the 33 to 11 kV circuit is a radial network, including open points between the primary sub-stations that allow continuity of supply in the case of transformer outages (Figure 2-2). Domestic consumers will normally be supplied from one of the three phases of the LV circuit. Many non-domestic consumers will have a 3-phase supply at 400V. Larger consumers or high-density housing, such as blocks of flats, may have their own distribution sub-station with a direct feed from the primary sub-station. For the purposes of this research, the LV networks are considered to be sub 11kV (i.e. the distribution sub-stations to the consumer, 400V 3 phase/ 230V single phase)[1]. Modelling the load in the LV networks is the focus for this work.

[1] The DNOs are responsible for networks below the 132kV level to the consumer connection point, up to and including the meter

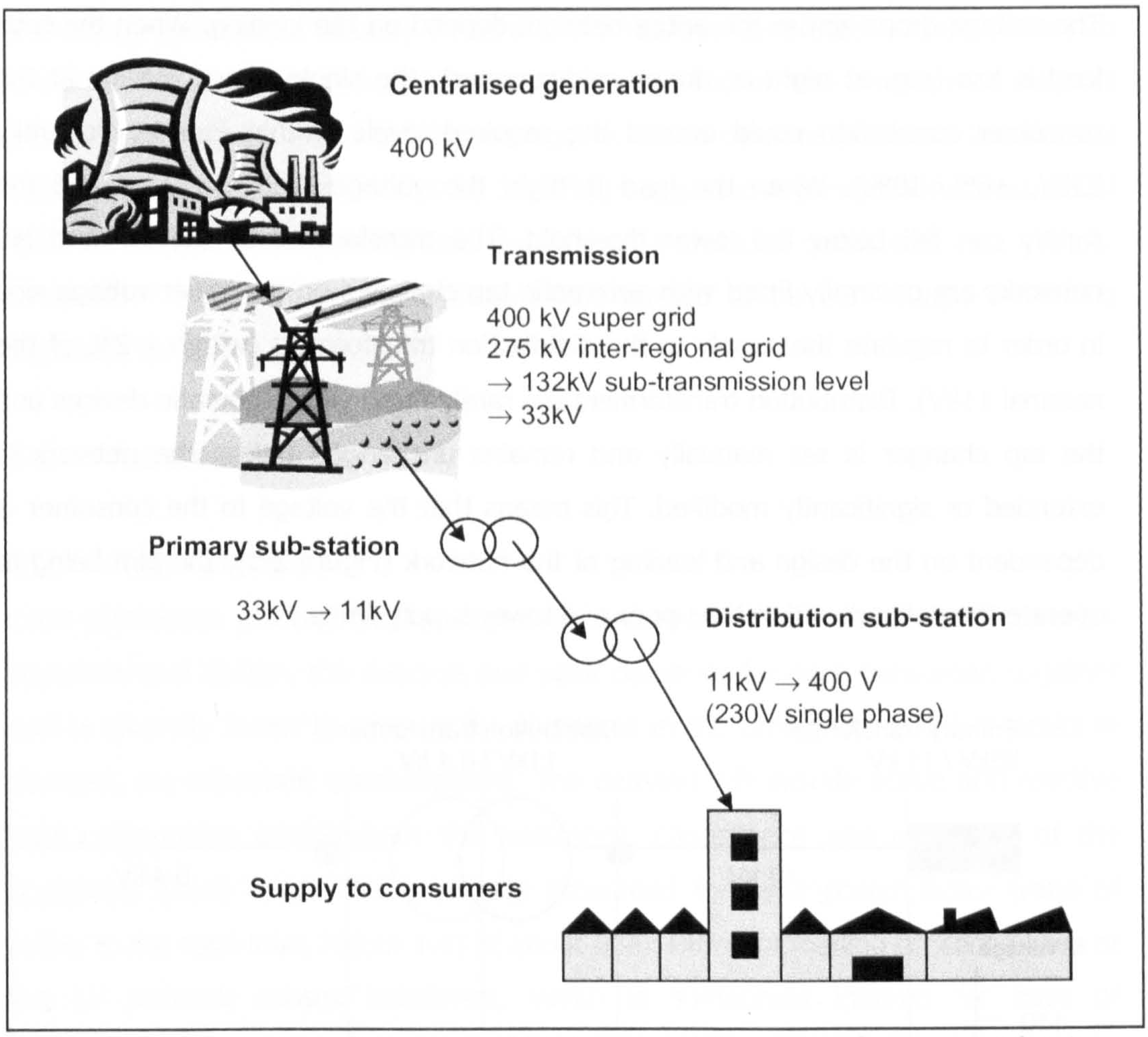

Figure 2-1: Illustration of the steps within the electricity system from generation to supply

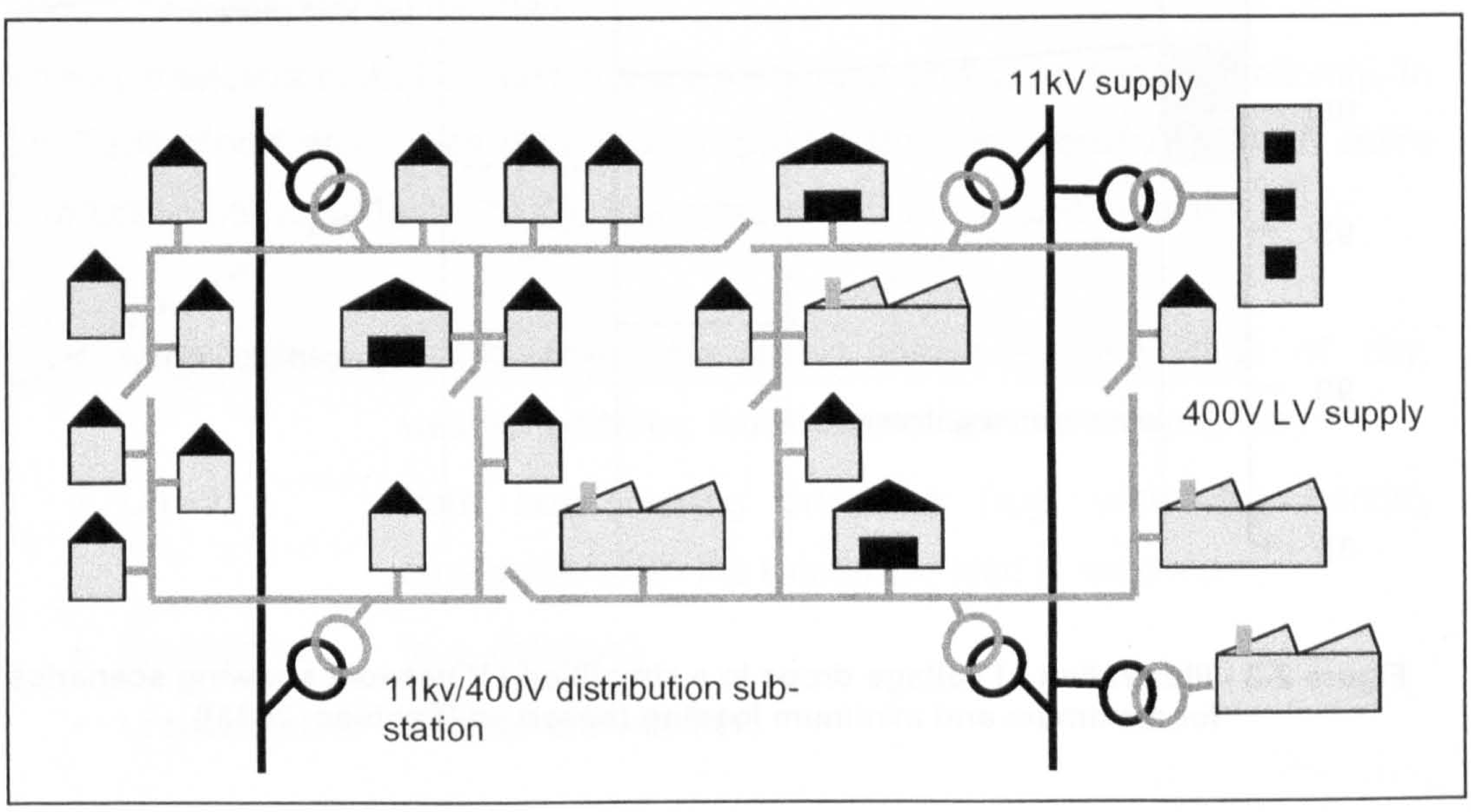

Figure 2-2: Typical LV 11kv/400V radial network (based on [Lakervi & Holmes, 1998])

2.1.2 Network operation

The voltage drops across the entire network depend on the loading. When the total load is low (e.g. at night or during mid-summer), the single phase voltage at the consumer connection could exceed the required levels (within Europe, generally 230V, +6%/-10%). When the load is high, the voltage drop increases and the supply can fall below the lower threshold. The transformers in the HV and MV networks are generally fitted with automatic tap changers on the lower voltage side in order to regulate the supply to the distribution transformers (within ± 2% of the nominal 11kV). Distribution transformers are rarely fitted with automatic devices and the tap changer is set manually and remains unchanged unless the network is extended or significantly modified. This means that the voltage to the consumer is dependent on the design and loading of the network (Figure 2-3), the aim being to operate the network within the upper and lower supply limits.

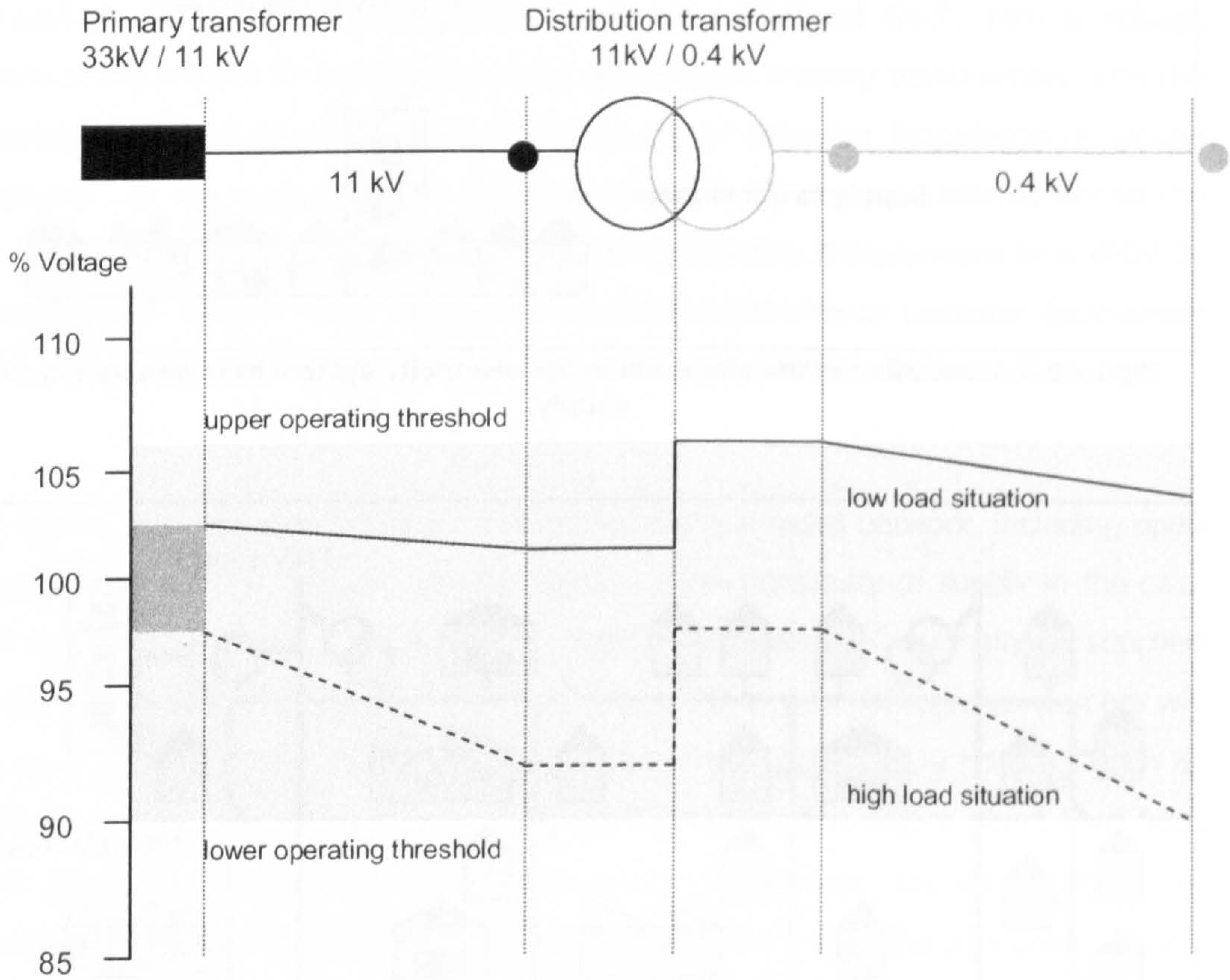

Figure 2-3 - Illustration of voltage drops in a simplified LV network showing scenarios for maximum and minimum loading (based on [Povlson, 2003])

In practice this situation works tolerably well. However in cases of high-density distributed generation, notably PV where the highest generated output is likely to coincide with the lowest levels of demand, the loading on the transformer may fall below the range for which the tap changer is set to operate [Povlson, 2003]. One study of a typical LV network [DTI, 2003(b)] suggested a penetration threshold of 48% for consumers exporting from small scale embedded generators (1.1 kW per connection node), where the limiting factor tended to be the voltage exceeding regulated limits.

2.2 The load

2.2.1 Nature of the load

Each connection point to the LV circuit represents a discrete demand. For network operation and design, the average and peak demands for each consumer, together with a diversity factor to account for variations in the timing of individual peaks in demand, are important considerations. The demand will include active and reactive load components arising from the resistance, capacitance and reactance of the appliances being used. This is usually accounted for by a power factor (ratio of active to the total load, Figure 1-4) of about 0.96. Different loading on each phase of the LV network causes imbalance, which is sometimes ignored for ease of calculation.

2.2.2 Factors affecting the load

Some parameters that affect demand are predictable and some behave randomly. In the Tesla model which was developed to predict the peak demand over an entire distribution network [Tesla, 2000], four categories of factors are included:

- Identifiable: arising from quantifiable influences (e.g. time of day, weather patterns, macro-economics or demographics)
- Latent: from slow moving processes (e.g. underlying trends), observable when the identifiable load is removed
- Exceptional: (e.g. holidays)
- Unpredictable: (e.g. severe weather)

The effects of day-light and weather-related factors are mostly obvious and are included in load predictions for scheduling generation. Building related factors – size, shape, location, etc. – are also frequently taken into account, notably for energy modelling [Shorrock and Dunster, 1997], and may be derived from GIS maps [Rylatt et al, 2001]. For domestic demand, occupant behaviour is believed to have a very significant effect. One study of heating showed that 80% of the demand variation arose from occupant behaviour [Olofsson et al, 1994]. Other factors such as age [Hitchcock, 1991] and occupant numbers [Robinson, 1997] have also been shown to have influence. A definition of the relationship between energy demand and socio-economic factors, such as income, has proved more difficult [Hitchcock, 1991].

For non-domestic buildings, identifying the influences is far more complicated with much more diversity in the use of electrical equipment and in the types of building occupied. Business activity clearly affects energy needs and electrical demand but for specific categories of business there can be a large spread in annual demand [Mortimer et al, 2000]. Energy use broadly increases linearly with floor area (the slope and scatter varying significantly with activity category) and this simple relationship is widely used in modelling energy demand for non-domestic consumers [Pout, 2000].

The electrical load for consumers with more than 100kW peak demand is metered on a half-hourly basis. As such, since measured data may be available to the network designer, the load models described in this thesis are not intended for the larger non-domestic consumers (although, as shown in chapter 8, the output is comparable with the metered data). The LRG has examined measured data to derive some averaged profiles for this group [Electricity Association, 2000]

2.2.3 Load description

The electrical energy in a network is generally described in kWh (or MWh) whilst network loading is usually considered in terms of power, or energy flow rate, in kW (or MW). Energy models tend to reflect the total annual consumption or demand per use of an appliance and are commonly applied in predicting the consequent emissions of greenhouse gases. Consumers using less than 100 kW peak demand are metered cumulatively and billed on the basis of monthly or quarterly energy usage.

The load for each consumer varies considerably with time. Whilst fuses or trips operate on an instantaneous level, digitised monitoring instruments sample the demand over a discrete time interval. For analysis purposes, the load is also averaged over defined periods. Consequently, to be meaningful, a power level in kW must be associated with a given time interval – the smaller the period, the greater the accuracy of capturing the time-varying characteristics. A longer time base causes the peaks to be cropped and the troughs to be filled (Figure 2-4)

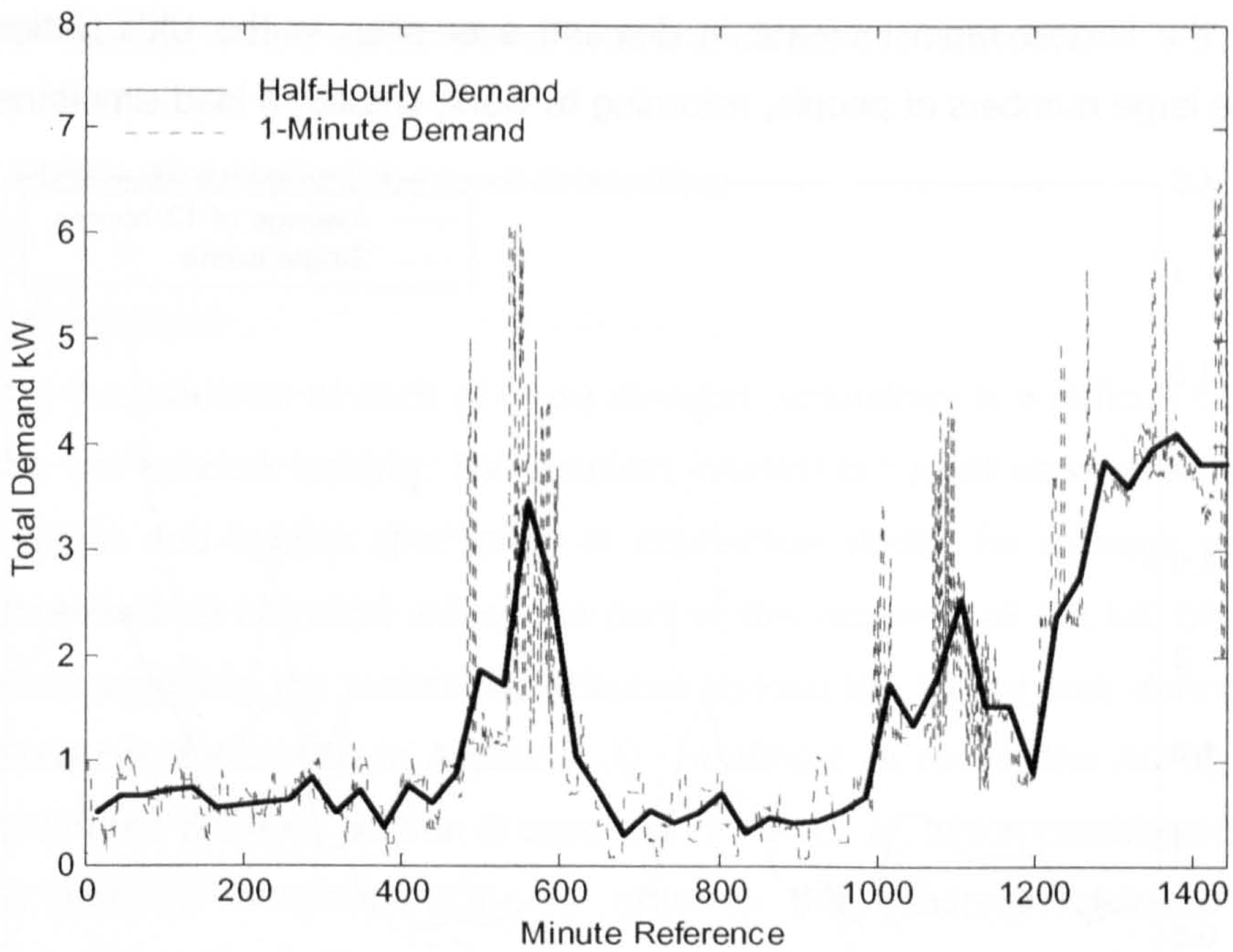

Figure 2-4: Comparison of load data averaged over one and thirty minutes (single dwelling, winter weekday – based on domestic dataset (2), Chapter 9)

Traditionally, half-hourly averaging of the load profile has been adopted in the UK for trading purposes[2]. Elsewhere, this is not considered sufficiently accurate for predicting demand; for example, in South Africa, the time interval chosen is 5 minutes [Nortje, 2001]. For investigating the start/stop behaviour of wind generators, a 2 second time-step is considered necessary [Bass, 1987]. Research into appliance demands [Newborough and Augood, 1999] investigated variations in time interval averaging from 1 second to 10 minutes and settled for the 1-minute

[2] The quality of supply, governed by the British Standard, BS EN 50160:2000, uses a 10 minute average for issues of voltage variation [BSI, 2000].

level. This was also chosen by McQueen for modelling residential demand in New Zealand, on the basis that it is the minimum duration for describing an under voltage event [McQueen, 2002]

2.2.4 Diversity

Diversity describes the variation in the demand for electricity between consumers within a group. When diversity is high, the group peaks and troughs will tend to be smoothed (Figure 2-5). When diversity is low, the demand is much spikier and the peaks are far higher. For example events following the solar eclipse in August, 1999 caused the largest rapid increase in demand ever seen in the UK's National Grid because large numbers of people, returning to work, created a load simultaneously.

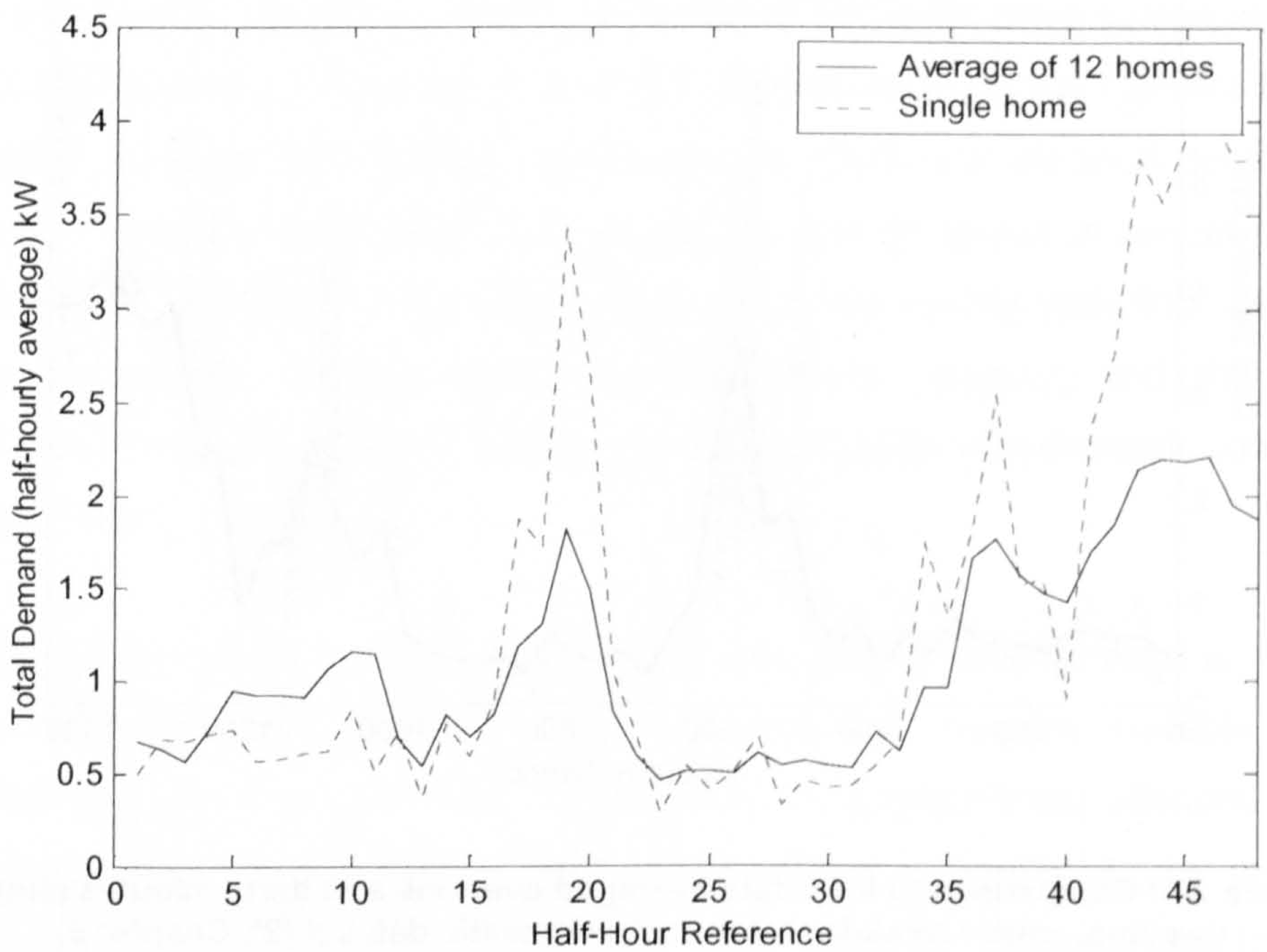

Figure 2-5: Comparison of demand for a single home and averaged over 12 homes (half-hourly, Winter weekday, based on domestic dataset (2), Chapter 8)

Within a group of consumers, the peak demand of the group is highly unlikely to equal the peak of the individual demands multiplied by the group size. It has long been common practice within the electricity industry to account for diversity using two elements – the After Diversity Maximum Demand (ADMD, the group peak in the demand per consumer) and the diversity factor (DF, the ratio of the actual peak demand for a group to that estimated from the ADMD). The maximum demand (MD) at a given supply node in the network is related to the DF and the number of consumers in a group, N, in line with equation 2-1:

$$MD = ADMD \times N \times DF \qquad [2\text{-}1]$$

When N approaches infinity, DF approaches unity and the ADMD and MD are considered equal. Estimates of the ADMD and DF, based on empirical data, are commonly used for design and development of the LV network. In practice, the demand of a single consumer is dependent on a wide variety of parameters and as such the diversity is very variable over time and across the network.

2.3 Methods adopted for load modelling

2.3.1 ADMD loads

Capturing the influence of each of these demand parameters is a difficult task when modelling the network loading. The simplest, crudest but most used method largely ignores them and applies spot loads at connection nodes for average and peak demands based on empirical values. As part of this research all the UK DNOs were questioned regarding the techniques adopted to load the LV network during design and development (detailed in Appendix A). In almost all cases, the ADMD method described in the previous section is used with a value, 'a', which combines the peak demand and the diversity factor to estimate the maximum demand at the transformer (Equation 2-2):

$$L = (a \times N) + d \qquad [2\text{-}2]$$

where:

L = total load for the group (kW)

N = number of homes in the group

a = ADMD x DF (kW)

d = loss and diversity allowance (kW)

The value for 'a' can vary with the size of the group (because of the variation in diversity between a small and large group), with the category of consumer (domestic, various non-domestic and industrial), with the nature of the end-uses (usually different values depending on whether or not electricity is used for water and space heating and for different tariffs) and with the size of the buildings within the group (usually number of bedrooms for domestic consumers and floor areas for non-domestics).

The degree of sophistication adopted by the various UK DNOs varies widely: some regularly account for all these factors whilst others generally ignore them, using the same value for 'a' throughout. Prior to privatisation, most of the DNOs used the same centralised methods and tools to develop the LV networks. Since then considerable variations have crept into the process with significantly different values for 'a' and 'd' being used. For example, for a group of 20 new 3-bedroomed homes using gas for space and water heating and an unrestricted tariff, peak demand estimates varied between 36 and 45kW (1.8 - 2.25kW per home). For 100 homes the estimates were between 148 and 225kW (1.48 - 2.25kW per home).

For larger non-domestic consumers (peak demand over 100kW), supplies are directly negotiated between consumer and supplier, with financial penalties if the demand exceeds the authorised supply capacity (ASC). Most DNOs take the ASC as the spot load at the connection point on the network. For new networks serving non-domestic consumers, the developer is usually requested to provide the DNOs with a list of typical demands (including appliances) and to identify unusual loads. Sometimes these loads can be greatly over-estimated by taking a highly conservative approach [Wright, 2004].

2.3.2 Peak demands from measured energy consumption

More accurate estimates of peak demand can be derived from the quarterly billing, using Verlander's equation (2-3):

$$P = k_1.W + k_2.\sqrt{W} \qquad \textbf{[2-3]}$$

Verlander's equation relates the peak demand per consumer, P (kW) to the annual electrical energy consumption W (MWh) using two coefficients, k_1 and k_2, which vary depending on the category of consumer (e.g. for domestic consumers, k1=0.29, k2 = 2.5; for commercial consumers, k1 = 0.25, k2 = 1.9) [Lakervi & Holmes, 1998]. This starts to present a more accurate picture of demand and diversity based on measured values. However in many situations annual consumption data may not be available.

2.3.3 Statistical variation of peak demands

Greater accuracy of the peak load estimates can be obtained from statistical representation of measured data since demand is essentially a stochastic process[3]. In the 1980s, the diversity in the half-hourly winter demand was researched for a group of UK domestic consumers [Nortje, 2001]. It was found that the spread of measured demands approximated to a Gaussian distribution. The results of this research are still applied by some DNOs as a feature of the design tool, DEBUT, which is widely used throughout the UK (Appendix A, Section A2.6) Such distributions do however allow the demand, as a mathematical artefact, to be negative, demonstrating the inadequacy of the model. Negative demands can only occur in practice if a connection node exports from a distributed generator, when a normally distributed demand is highly unlikely.

Professor Herman approached the problem of estimating the peak voltage drops in networks when electrification was extended to disadvantaged areas of South Africa in the 1990s [Herman & Gaunt, 1997]. He adopted a beta distribution, described by two indices that vary the skewness and a maximum current (usually the rating of the fuse or circuit breaker). This provides a bounded distribution eliminating the problem of false negatives, which can be skewed to suit different types of consumer (Figure 2-6). The Herman-Beta method[4] of estimating peak voltage drop is commonly used in the South African electricity industry and is a feature of the ReticMaster network design tool for load representation [Nortje, 2001]. Capital cost savings of up to 7% have been observed over the ADMD method when the two indices are optimised to specific network situations [Ferguson & Gaunt, 2003].

Using either the normal or beta distributions allows for a more accurate representation of diversity between consumers beyond using the same value for

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[3] The definition of a stochastic process is taken here as a process that depends on random variables which are in turn dependent on a variable parameter, in this case time.

[4] For the Herman-Beta method, a random assignment can be made for the peak current rating for each consumer, using the cumulative probability densities of these beta distributions. By selecting a probability for the y value, the x value gives the ratio of the assigned current to the maximum current (which is the fuse rating, generally 20 amps in South Africa)

peak load at all connection points. Such methods introduce a random element for estimating the peak loading along a feeder.

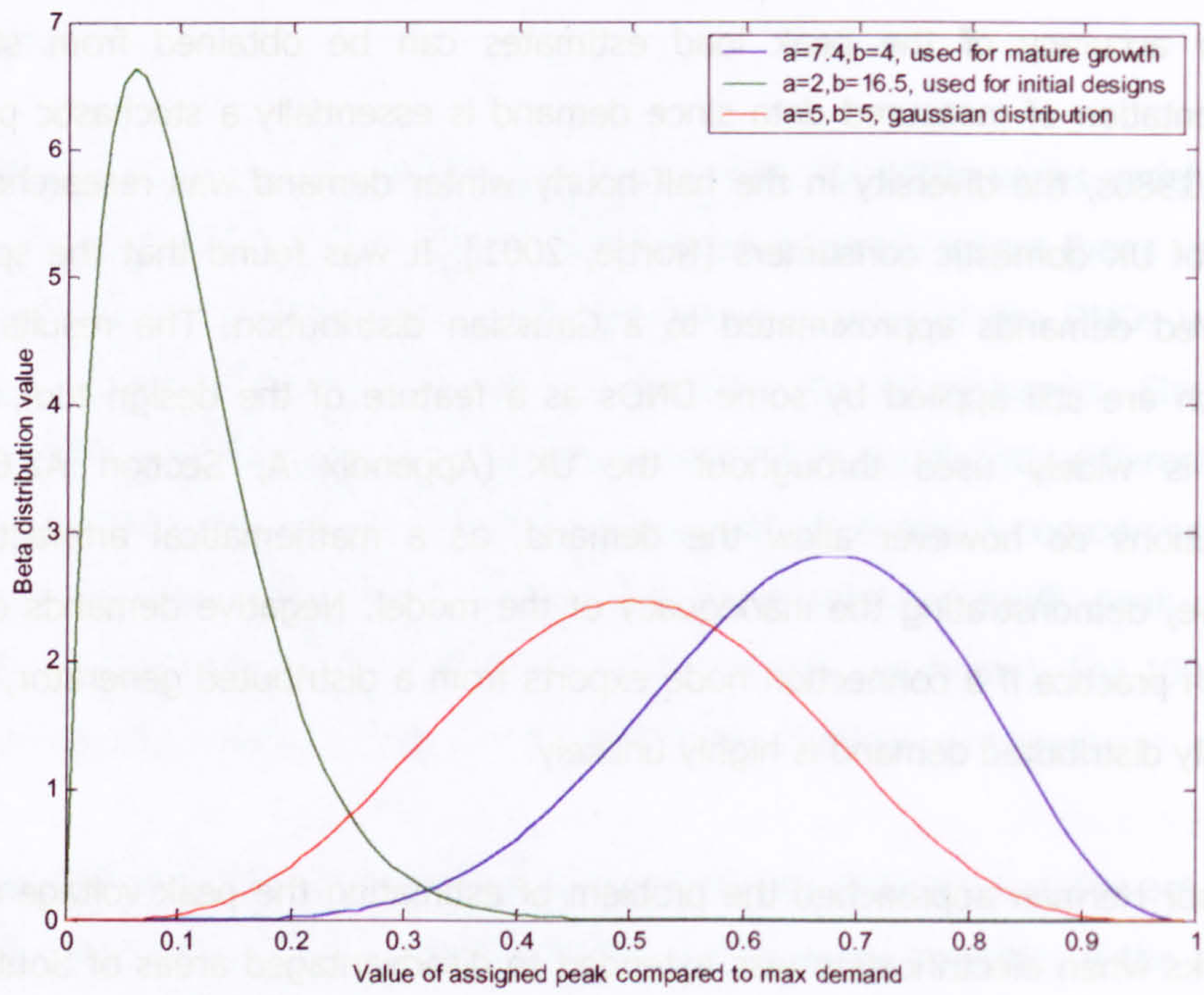

Figure 2-6- Examples of beta distributions using skewness factors adopted for new and existing networks (the Gaussian distribution is a special case, where the skewness factors are equal)

2.3.4 Daily load profiling

Driven by the need for accurate trading, following the trend towards privatisation of the energy industries in the late 1990s, more detailed metering for different kinds of consumers, usually on a half-hourly or hourly basis became a key area. Within the UK, such data were provided commercially by the Load Research Group (LRG) of the Electrical Association [Electricity Association, 1998(a)]. In other countries similar databases exist for example, MAISY [MAISY, 2004]. Whilst some are freely available they are of limited use outside the countries of origin, usually Canada or America.

Typically, either these databases or those directly metered by the utilities can be used to provide a set of regression models with coefficients for day of week, season and time of day which provide a distinct half-hourly profile for each day of the year (sometimes simplified into seasonally averaged profiles, Figure 2-7). However, such highly averaged group profiles provide patterns of demand but do not give an indication of the diversity and the spiky nature of the load profile for an individual consumer.

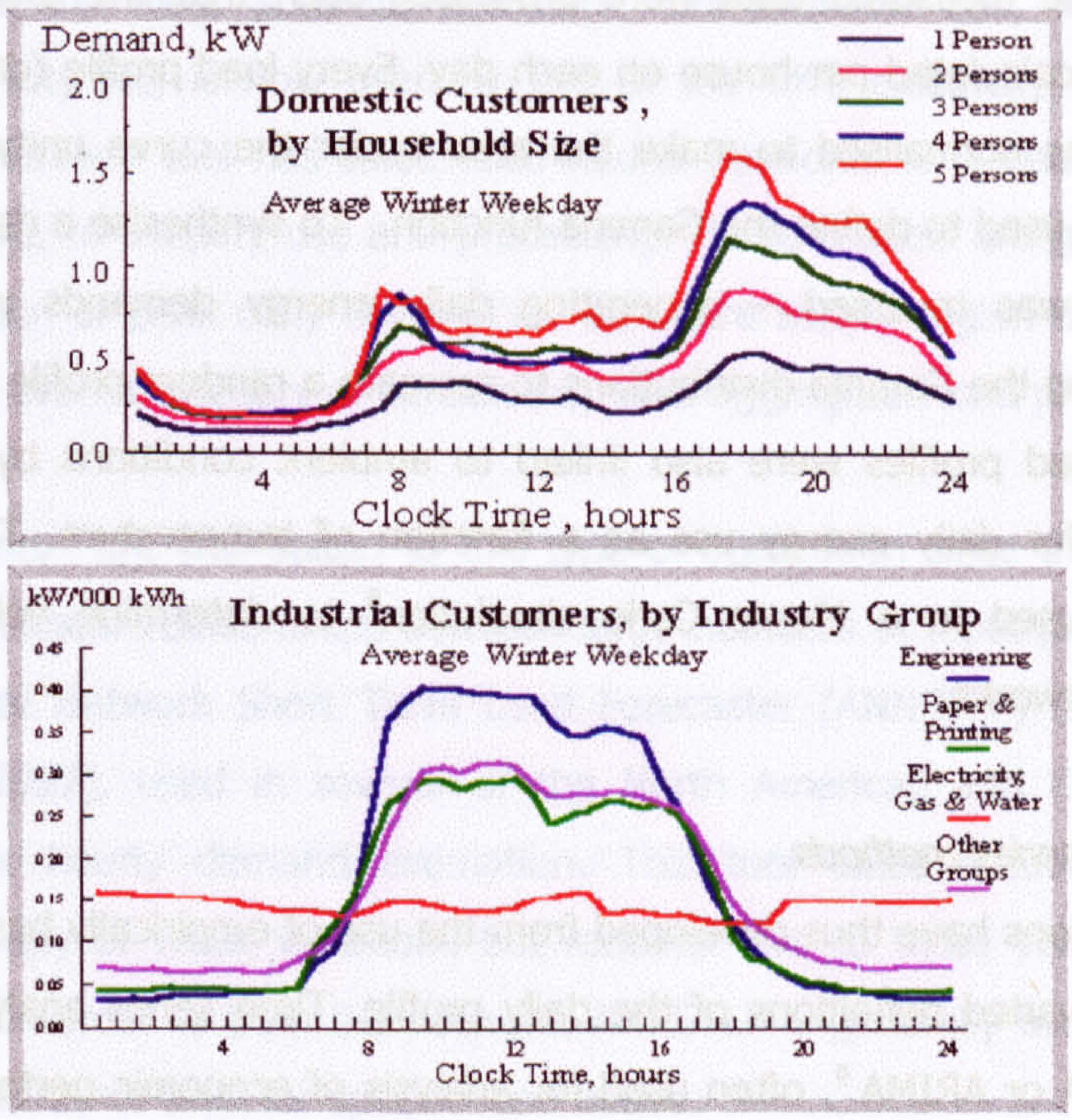

Figure 2-7: Examples of daily load profiles from the LRG (Domestic and Non-Domestic consumers, half-hourly averages)

2.3.5 Statistical variation of daily load profiles

In South Africa, concerns over the power quality for networks extended into remote rural regions also led to the development of the Integrated Planning Solution (TIPS). The importance of load description beyond the peak level was recognised and a database of generic daily profiles was created – largely for domestic consumers. These profiles may be scaled to account for long-term trends in demand and linked to environmental and socio-economic factors to provide greater accuracy for network loading [Jones et al, 1999(a)].

Research in New Zealand examined the daily demand patterns of domestic consumers and investigated the variation between consumers on a given day and from one day to the next for individual consumers. Several methods were investigated for generating a stochastic daily profile of demand from data measured in 21 homes, including Fourier Transforms[5], Markov chains[6] and Poisson Rectangular Pulses[7] [McQueen, 2002]. For examination of the performance of a typical LV network, a method based on a Gamma distribution was finally adopted [McQueen et al, 2003]. The measured data were processed such that the total daily energy demand was calculated per house on each day. Every load profile (daily, half-hourly averaged) was normalised to make the area under the curve unity and the half-hourly values used to define the Gamma function. To synthesise a daily load profile, the process was reversed – generating daily energy demands and half-hourly demands using the Gamma distributions to recreate a random profile per connection point. The load profiles were also linked to ambient conditions by adjusting the mean value for daily energy use as a function of temperature. The model was successfully used in a Monte Carlo simulation[8] to determine voltage drops in residential networks.

2.3.6 Time series methods

Load descriptions have thus developed from the use of empirically based spot values to randomly varied definitions of the daily profile. Time series analysis techniques such as ARMA or ARIMA [9], often used for analysis of economic performance (which similarly has both predictable and random components), go a step further in describing the continuously varying demand. Bass [Bass, 1987] in his work to size generators for island communities provided a methodology for creating a more accurate synthesized load profile from measured data for demands (other than for cooking or heating).

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[5] Fourier analysis is the decomposition of a periodic function into the sum of the sinusoidal components

[6] A Markov chain is a random process where the probability of a future event occurring is related to the present state (or immediately preceding) but not on events that led up to the present state. A Markov process is said to be 'memory less' and occurs over a defined time period and has a defined number of possible outcomes.

[7] Poisson Rectangular Pulse concept involves breaking demand for a single consumer into discrete demands that are constant for a period of time. A Poisson event has a probability of occurring that is independent of time – hence based on a Poisson distribution.

[8] Simulation method using statistics to utilise sequences of random numbers

[9] ARMA is Autoregressive Moving Average, ARIMA is Autoregressive Integrated Moving Average; both are methods of predicting future events from knowledge of the past.

Similarly, the Tesla model (described earlier) adopts a variety of statistical techniques, including time series and probabilistic methods, to identify patterns using previous measured load data and records of various weather parameters. It is claimed to be the most accurate prediction tool available and, developed with London Electricity plc, is now used by five of the UK's electricity providers. The SMART Weathervane tool has since used neural networks as a basis for a model related to Tesla, to simplify use and processing. These models are generally aimed at the prediction of peak daily demand for an entire supply region down to a local sub-station or even a category of consumers, from aggregated load profiles.

Neural networks[10] are well suited to this type of application since they are able to cope with non-linear relationships between large numbers of input parameters. The Artificial Neural Network Short Term Load Forecaster (ANNSTLF) is one example [Khotanzad, 1997], used in several of the North American and Canadian utility companies for hourly demand estimation. This tool takes account of weather patterns and day of week variations but requires two to three years of previous demand data in order to train the network. ANNSTLF is generally used over a large network region rather than for specific load nodes.

2.4 Bottom-up load modelling approaches

2.4.1 Importance of bottom-up load modelling

Whilst the time series approaches can provide very accurate models of the network loading, they depend on the availability of previous data and are essentially black-box applications. To investigate future 'what-if' scenarios, especially those that involve considerable uptake of solar RETs, requires a good grasp of the underlying causes of the demand and hence diversity. Modelling demand on a bottom-up basis provides exactly this, allowing the user to modify and extend the load simulation using recognisable components.

[10] Neural networks were originally designed to mimic the human brain – by comparing the output for a group of inputs and adjusting the gains as a series of nodes. This is similar to way in which neurons pass electrochemical signals in the human brain. Networks must be trained with one data set and then validated with another.

2.4.2 ADMD values for different end-uses

The importance of incorporating end-use into load modelling was recognised as early as the 1940s [Arvidson, 1940]. Arvidson investigated nine different end-uses for domestic consumers, each with an hourly variation factor to describe the use pattern during a typical day. He assigned a linear relationship between the ADMD and the number of consumers for each end-use category. The ADMD could be related to factors including ambient temperature, built form, number of occupants, occupant behaviour and technical details of the water tank, boilers, etc. Arvidson's work became part of the industry working practices in the 1960s.

In his work in Australia to provide econometric models for energy demand, Bartels [Bartels & Fiebig, 2000] identifies the importance of end-use models for policy making in terms of reducing domestic energy demands:

'They are the only demand-modelling tools capable of analysing the impact of technological change or policy initiatives with respect to particular appliances.'

Bartels went on to apply some novel metering techniques to identify domestic electrical demand for nineteen different end-uses.

2.4.3 Demand Side Management

Demand Side Management (DSM) became an area of interest in the UK in the 1990s, partly because sophisticated domestic metering and tariffs were not adopted as in other parts of the World. Understanding appliance profiles and patterns of use can serve to develop strategies to crop peaks in demand, easing the potential problems of insufficient generating capacity. Newborough and Augood [Newborough & Augood, 1999] gathered daily demand signatures for most domestic appliances and were able to reduce peak demands by as much as 60% through adoption of 'load conscious' controls. Various strategies were examined which adjusted the mix of appliances, the timing of use or the control algorithms.

In practice, DSM tends to be used for storage heating, where charge start times are varied over a region to reduce the peak load. Interest in DSM has waned over the last ten years as the electricity industry became split, with different groups for generation and distribution [Wright, 2004].

2.4.4 End-use demand measurements

To provide a better understanding of the load and partially to support efforts to reduce energy consumption, the LRG made detailed measurements of domestic and non-domestic end-use demands [Electricity Association, 2000]. The project was started in 1992 when nine different types of appliance were investigated on a half-hourly basis. In 1996, investigations were conducted into storage and water heating, followed in 1996/7 by a review of lighting demand. Whilst total demand (split between consumers on an unrestricted as well as off-peak tariffs) were taken from an integrated database of 1200 consumers, end-use and appliance demand values were based on a variety of projects, covering different samples of consumers over varying periods of time. 175 individual appliances have been monitored by the LRG in the total group of homes, with up to 100 samples in each category. Using the statistical methods developed by Bartels [Bartels & Fiebig, 2000], the LRG were able to provide an assessment of the relative contribution of end-use demands to the total (Figure 2-8). The LRG data forms the basis of the first layer of the domestic model and will be discussed further in chapters 3 and 4.

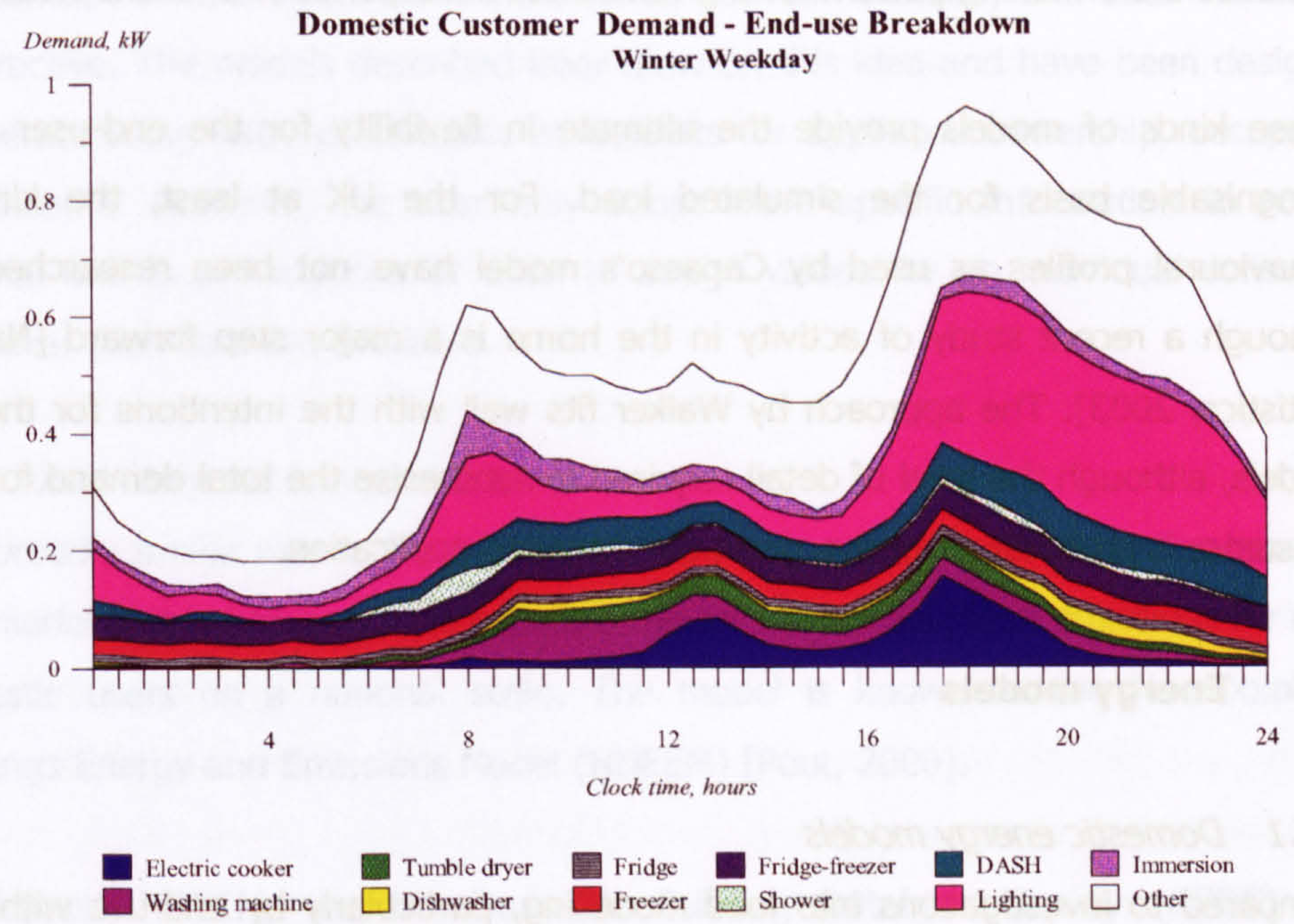


Figure 2-8: Total and end-use domestic demands for a typical winter weekday (half-hourly averaged, group averaged, unrestricted tariff, ambient 42°F from [Load Research, 1999])[11]

[11] DASH = direct acting space heating

2.4.5 End-use simulations

Since a large part of the diversity in domestic demand arises from the variation in occupant behaviour, one of the advantages of adopting a bottom-up approach is that human influences can be varied for each end-use. In Italy, a domestic load model [Capasso et al, 1994] was developed to include some element of psychological behaviour for different household types. The model defines times of the day when particular occupants would be at home. Associated with this is a probability pattern for different activities. Appliances, with known duty cycles, are assigned to each activity. The combination of occupancy, daily activity profiles and appliance demands resulted in a simulated daily load profile. Behaviour patterns were established from national data for various household members (based on age, income and gender).

Similarly a residential load model was constructed [Walker, 1982] by considering an availability function, which identified the probability that someone is available to switch on an appliance, a proclivity function, which indicates the probability that the person will switch it on at a given time, and the normal-cycle function, which identifies the switching pattern for a given device in response to ambient conditions.

These kinds of models provide the ultimate in flexibility for the end-user and a recognisable basis for the simulated load. For the UK at least, the kinds of behavioural profiles as used by Capasso's model have not been researched fully although a recent study of activity in the home is a major step forward [National Statistics, 2003]. The approach by Walker fits well with the intentions for the load models, although the level of detail required to synthesise the total demand for each consumer is probably excessive given the intended application.

2.5 Energy models

2.5.1 Domestic energy models

Compared to investigations into load modelling, particularly by end-use within the UK, research into total energy demands has been much more prolific. The Building Research Establishment Housing Models for Energy Studies (BREHOMES) [Shorrock & Dunster, 1997] are the most commonly used domestic energy models in the UK. Whilst the BREDEM-12 models are for annual energy predictions, the BREDEM-8 model [Anderson et al, 1997] provides monthly estimates. The model predicts energy demand and carbon dioxide release from space heating, water heating, cooking, lighting and appliances. BREDEM-8 takes into account many building-related factors but very limited relationships with occupants and their behaviour. The BRDEM-9 model is widely used as the basis for Standard Assessment Procedure (SAP) ratings which are used within the UK building regulations.

In practice, it is often costly in time and money to gather all the required data (nearly eighty input parameters) for a full BREDEM-8 calculation. Gadsden's models for the Enlightened Planning project [Gadsden, 2001] adopted various defaults derived from national and regional statistics, allowing the BREDEM-8 models to be used even when data was difficult to obtain. Similarly, the National Home Energy Rating (NHER) tools provide different levels of energy estimation, based on BREDEM-12, and are widely used by UK local authorities for energy demand estimation [Chapman, 1994]. There is of course a trade off between the cost of data collection and the accuracy of the output.

The concept of user selection in the balance between accuracy and data availability is attractive. The models described later draw on this idea and have been designed to operate using national statistics as defaults for appliance ownership, occupancy and income. However, the user may adopt more specific information to reflect regional and local variations or even to assign values for an individual consumer whenever such data are available.

2.5.2 Non-domestic energy models

In a broadly similar way to the BREHOMES domestic models, recent studies have led to a model that is being used to estimate the annual consumption emissions for non-domestic users on a national scale. The model is known as the Non-Domestic buildings Energy and Emissions Model (NDEEM) [Pout, 2000].

To support NDEEM, the Non-Domestic Building Database Survey (NBDS) was conducted [Steadman et al, 2000]. Data was gathered from four UK locations and was supplemented with records from the Valuation Office of the Inland Revenue[12]. This research provided a much-needed expansion of energy modelling into the non-

[12] UK tax gathering organisation

domestic sector. Data from NDEEM regarding typical annual consumptions, the proportion typically provided by electricity and the relative demands by end-use have been used to develop the non-domestic electricity load models, described in Chapter 7. However, there are no per building non-domestic models comparable to the BREDEM range of models for dwellings.

A number of other models have examined urban energy demand, including the Dynamic Regional Energy Analysis Model (DREAM) applied in the DREAM-City tool [Titheridge & Boyle, 1995], the Energy and Environment Prediction model [Jones et al, 1996] and LT-Urban [Ratti et al, 2000] for non-domestic buildings. These models tend to estimate energy demand on a monthly or annual basis. Two further energy models attempt to estimate demand on a half-hourly basis: ESP-r and Sustainable City.

2.5.3 Half-hourly averaged energy models

ESP-r provides a very comprehensive set of tools designed initially for architects and building service engineers [Clarke et al, 1998]. As part of the bSmart process, it assists with the design of buildings to incorporate RET. Within bSmart the EnTrack module provides the demand scenario. EnTrack is capable of inputting metered data and using time series analysis to derive demand profiles. ESP-r is a very detailed model that is probably best suited to assessing the energy demands of an individual building.

Another energy model, Sustainable City (EPSRC Project GR/L04863), investigated energy flow and pollution in cities [Halliday et al, 2001]. This project studied half-hourly data at the primary feeder level, for regions of Leicester City, comparing the different transformer load profiles and examining the associated mix of consumers. The project looked briefly at strategies for demand-side management (in terms of tariffs) and demand reduction (such as low voltage light bulbs), centred on energy flow rather than electrical networks. The Sustainable City study was partly based on the same LRG half-hourly domestic demand data as the models for this research. However, the approaches are quite different, as described further in chapter 4.

2.6 Network design tools

(A summary of features for the main network design/development tools available is presented in Table 2-1)

2.6.1 UK industry practice – WinDEBUT

Of the seven DNOs who responded to the User Needs questionnaire, five were using the tool WinDEBUT to design or develop the LV network (Appendix A, Section 2.6). To load a network, WinDEBUT adopts the ADMD approach described earlier (Section 2.3.1). The tool (Figure 2-9) also allows users to select daily load profiles from a database, supplied from the LRG data. These profiles cover domestic and different categories of non-domestic consumer, based on tariff, business activity and load factor ranges[13]. These profiles are group averages for different day types and for each season. For unusual loads, the user applies a spot load (peak value and power factor) or linearly distributed loads in kW per metre. The latest versions of WinDEBUT also allow users to select from a database of daily profiles for nine distributed generators. All of these profiles operate on a half-hourly basis.

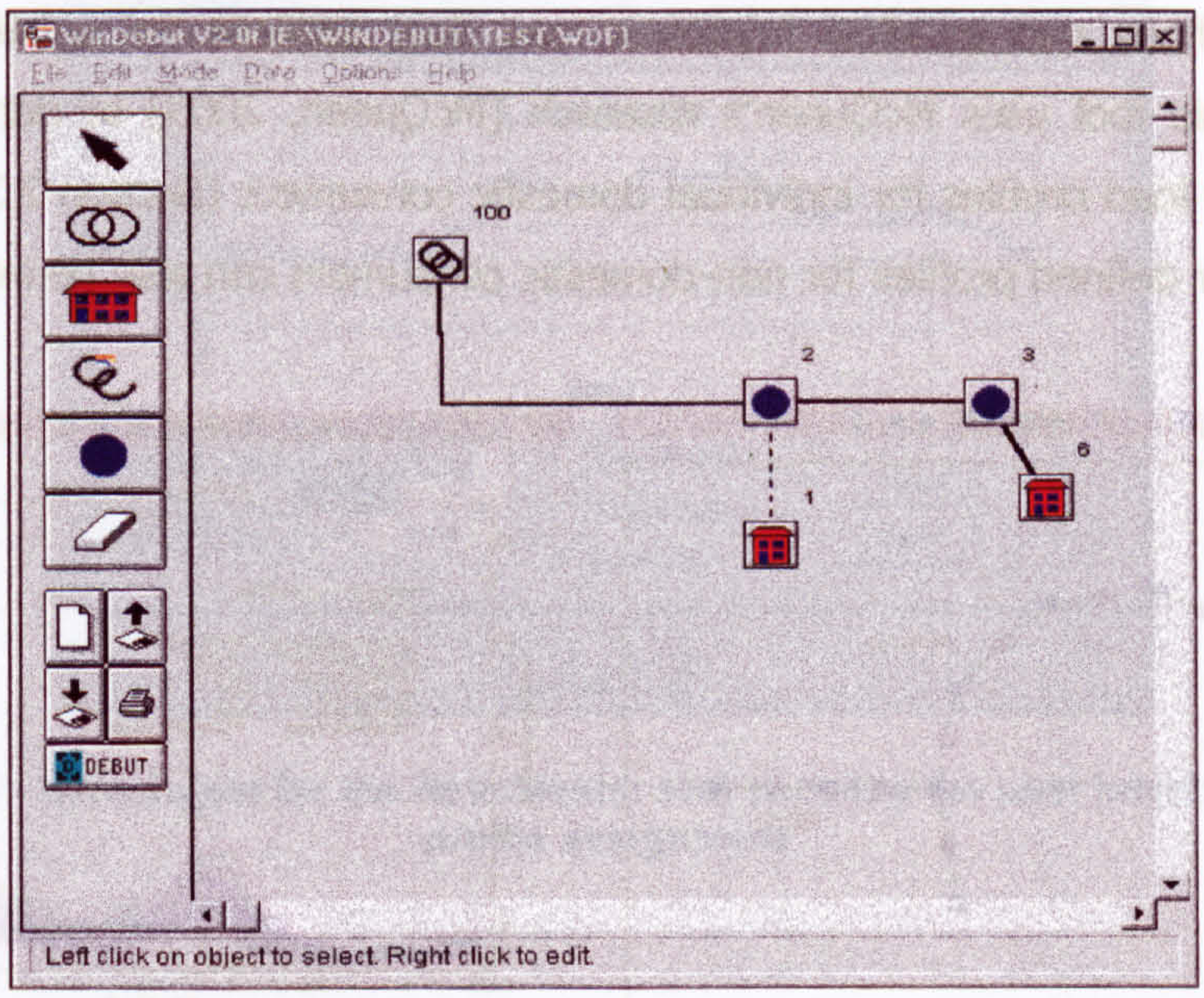


Figure 2-9 - Screenshot from the WinDEBUT tool

[13] the load factor is the ratio of the average to the peak load over a given time, categories are >20%, 20-30%, 30-40% and >40%

2.6.2 Other UK approaches

Two of the seven DNO responses indicated use of the PSS packages from Shaw Power Technologies Incorporated (PTI) of the USA [Shaw PTI, 2004]. The PSS suite of tools provides the facility to examine in detail the performance of the electrical networks, for looped or radial designs, in phase balanced or unbalanced conditions. The PSS-ADAPT package is especially suited to analysis of the LV circuits – allowing users to identify different motor start-up conditions for industrial consumers. The PSS/E tool tends to be used for high to medium voltage circuits with a library of generator models that can be adapted by the user to represent centralised generation. Loading of networks for the PSS tools is either by spot loading or linearly distributed loading of branches. Users also have the facility to input from files – from a library of load profiles or metered data. One of the DNOs questioned used the WinDEBUT load models within PSS-ADEPT. Other packages including IPSA and DINIS are used in the UK for medium to high voltage networks.

2.6.3 Tools used outside of the UK

The Residential Network Optimisation tool (RiNO, Figure 2-10) was developed in New Zealand to improve the accuracy of the load estimation beyond the simple ADMD methods and to allow improved load flow analysis for unbalanced phase loading. This tool uses McQueen's research [McQueen, 2003] to derive randomly varied daily load profiles for individual domestic consumers (Section 2.3.5). Metered data or user defined profiles for non-domestic consumers can also be introduced.

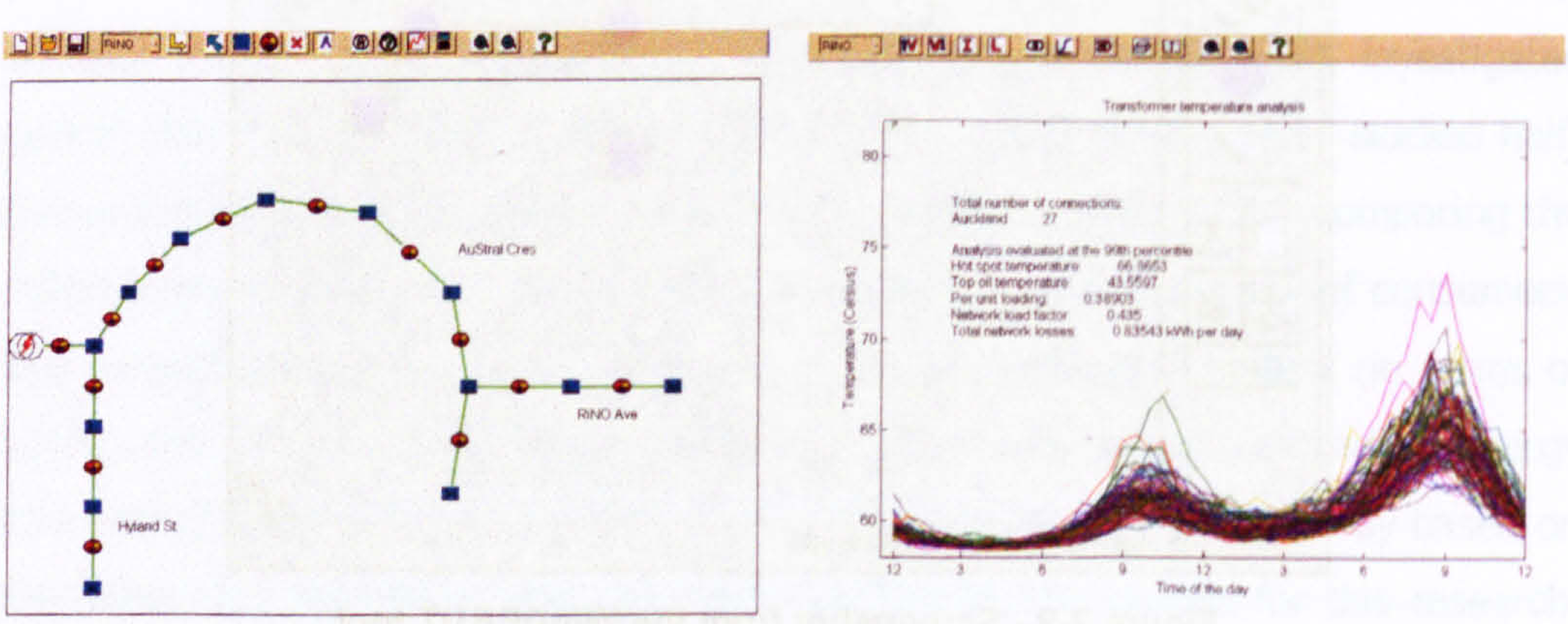


Figure 2-10: Screenshots from the RiNO tool showing network layout and transformer temperature performance output

ReticMaster from Inspired Interfaces of South Africa. [Inspired Interfaces, 2001] is part of a suite of tools for network design and is specifically for radial networks, from high to low voltages. The user may define loads, applying scaleable spot or bulk loads. Daily and annual load profiles are provided for different categories of consumer (Figure 2-11). Domestic loads may be derived empirically or stochastically, using the Herman-Beta method (see section 2.3.3).

Advantica's SynerGEE tool is widely used in Canada and the USA [Advantica Inc., 2003]. The tool claims realistic loading of the network on an hourly basis. Thirty-six daily profiles are provided in each consumer category for different days of the week, each month of the year and for the peak day of each month (Figure 2-12). Measured data may also be imported. When the user selects a time span over which the network performance is to be evaluated, the tool automatically switches between the appropriate daily load profiles to improve the accuracy of the results.

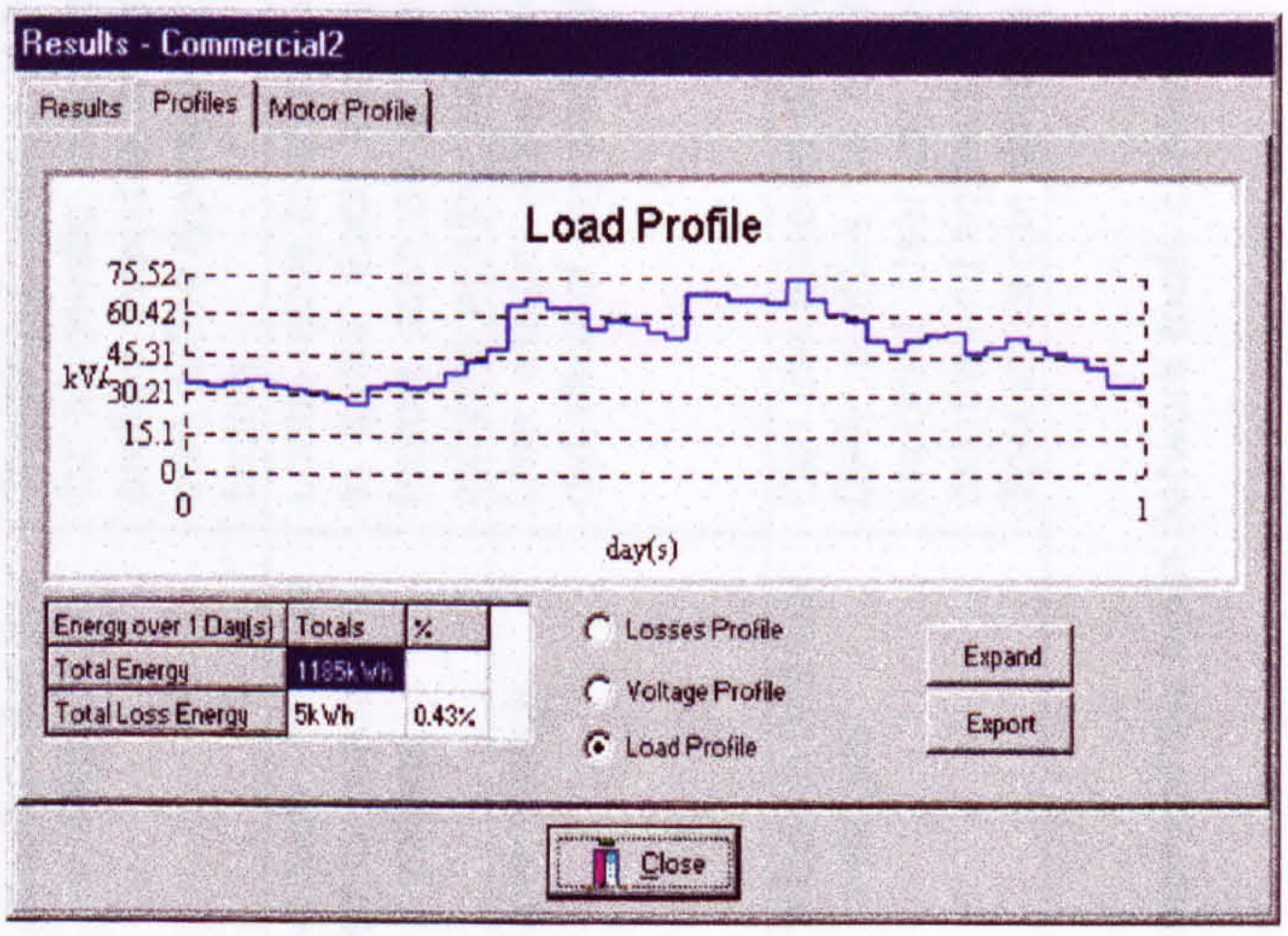


Figure 2-11 - Screenshot for the ReticMaster tool showing the user interface for load profile assignment

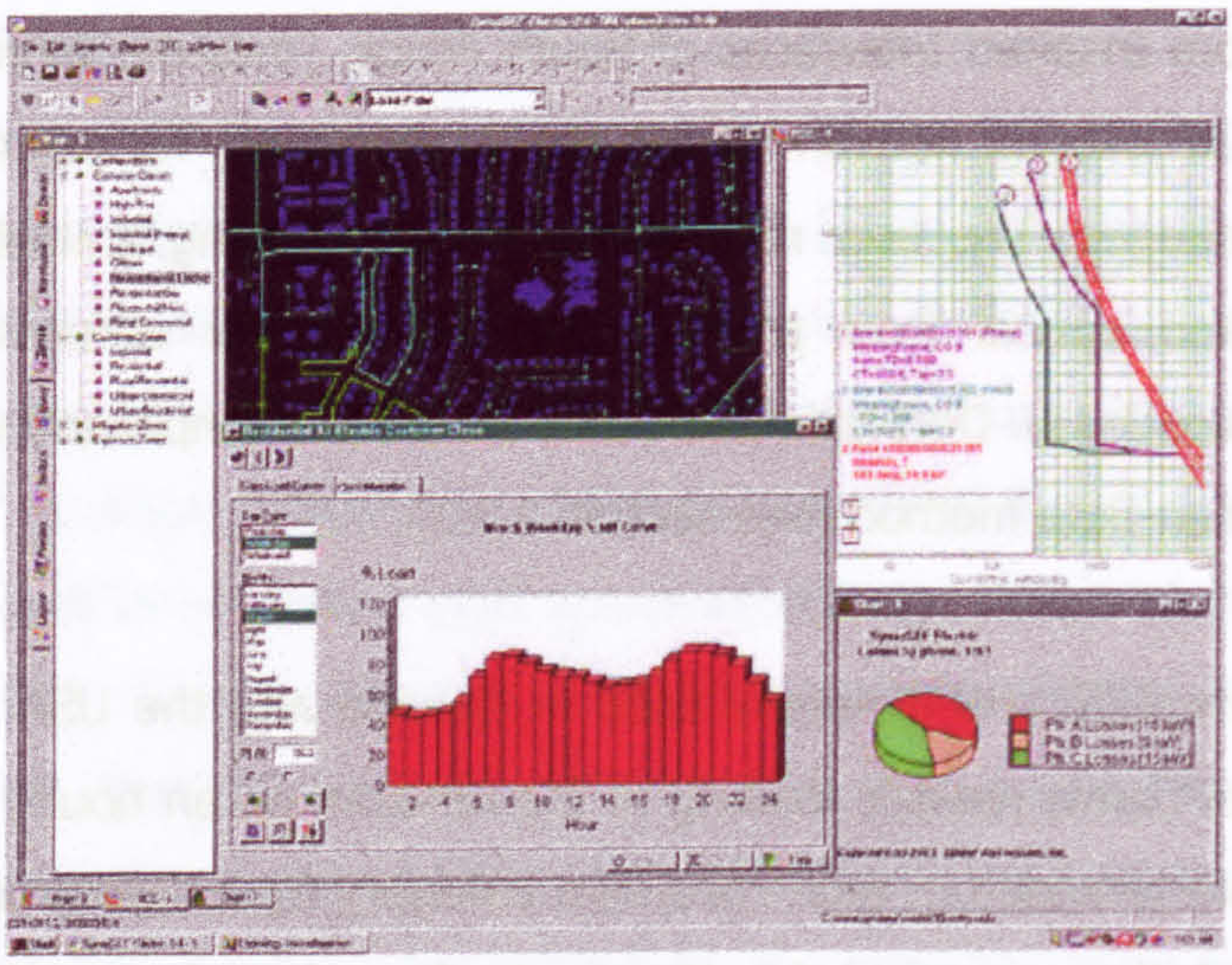


Figure 2-12: Screenshot of the SynerGEE Electric tool, showing screen for user modification of a load profile

Tool	Supplier	Network scope	Load representation	GIS based	Usage
RiNO	Austral EA Ltd., New Zealand	Low voltage	User defined profiles for residential, commercial and undiversified loads. Input of metered data with RiNO model used to provide stochastic daily profiles for domestic users	Not specifically – although export of files is possible	Used by Austral EA for consultancy work in Australia and New Zealand
ReticMaster	Inspired Interfaces, South Africa	High, medium and low voltage	Traditional method (ADMD, DF) or Herman Beta method for stochastic assignment. Libraries of annual or daily profiles available that can be scaled by user. User may also define typical daily or annual load profiles and power factors	Can be linked to GIS	Widely used in South Africa (Can operate with PSS/U)
EaNSF	EA Technology, UK	Low voltage – may be used for medium voltage	Loads relate to annual consumption, from a library related to tariffs. Each load is user scaleable. User may vary factors such as ambient temperatures and frequency of extreme weather events	May be linked to GIS	Widely used in the UK electricity companies
WinDebut	EA Technology, UK	Low voltage	User assigns point loads based on consumer type, with definition of day and night time demands	May be linked to other systems, including GIS	Commonly used by UK electricity LV network operators
SynerGEE	Stoner Associates, PA, USA	High, medium and low voltages	Can use metered data (kVA) or annual billing data (kWh). Daily profiles on an hourly basis may be created or imported. User can select profiles for different weekdays, months and adjust the hourly values. Spot loads can simulate heavy users or equipment	May be integrated into a GIS	SynerGEE software widely used by utilities in the USA. Available in Europe, usage unknown.

Table 2-1 : Summary of the main network tools currently available, detailing the way in which load is modelled

Tool	Supplier	Network scope	Load representation	GIS based	Usage
DINIS	ICL, UK	Medium and, rarely, low voltage	User definable profiles or selection from a library of 200 typical load profiles. Daily profiles, with variation for weekends may be assigned at supply nodes	Can use a paper map background or links to GIS	30 companies worldwide, including most of the UK electricity providers
PSS /ADEPT /E /O /VIPER /Engines	Power Technologies Inc., USA	High and medium voltage, generator modelling (PSS/VIPER used for single line networks, e.g. marine and small industrial uses)	Manual input of loads (allows scaling of point loads to achieve the correct upstream value)	Generally no – PSS/VIPER links to GIS and PSS/Engines can be GIS embedded	PSS/E Widely used by electricity industries PSS/ADEPT replaced PSS/U which had limited use in the UK PSS/Engines not generally used in UK
IPSA	IPSA Power Engineering CAD Ltd., UK	High voltage (occasionally used for Medium voltage), generator modelling	Manual input for single supply point load	No	Many of the UK electricity providers
ERACS	ERA Technology, UK	High/Medium Voltage	No information available. Thought to be manual entry – from database	No	No major supply companies – industrial and academic users
Power World	Power World Corporation, USA	High Voltage	Manually entered figures for supply point loads	No	USA

Table 2-1(continued)

2.7 Assessment of existing models

2.7.1 Need for improved realism

At the start of this chapter, we began by looking at some of the problems associated with capturing the characteristics of the electrical load. Whilst simple methods of load assessment using ADMD values, have proved adequate in the UK so far, the introduction of embedded RETs, especially solar technologies, calls for a more realistic and detailed description of the network load.

Very dramatic changes can occur in the output of PV, sometimes from 10% to 100% of peak power and back again, over very short timescales. Coincidences of high PV output with low demand are possible and understanding the resulting sharp peaks of export power is likely to be key to the design of suitable LV distribution systems. Typically in urban areas, high densities of PV can be installed in selected communities, each panel with a similar orientation and location. For example, a row of houses on the south facing side of a street might all have PV panels which export simultaneously, even connected to the same phase of the network. The scale of the exported power is unlikely to be very different to that of the typical supplied power (PV maximum export is likely to be around 2kW per dwelling), giving a power flow of similar degree but reversed. However, the load could suddenly fall below that for which the tap changer within the distribution transformer is set to handle and the voltage could exceed the required threshold. Whereas network designs were previously based on absolutes – it either works or fails – the modern approach is to assess the risk of failure and to examine the compromise between cost and quality of performance. The load models described in this research, as a package with load flow analysis (Thomson et al, 2003), facilitate investigations of the statistical probability and duration of network operation outside intended targets (over-voltages and over-heating) and the likely locations for such events.

2.7.2 Capturing the load and diversity variations over time

The models described in the next chapters aim to provide a simulated load at each connection point, capturing most of the features of diversity. The time base for the models has been chosen as 1-minute averages, in line with previous research [Newborough & Augood, 1999; McQueen, 2002], thus providing simulations of the varying degree of diversity with time. Using a 1-minute interval for RETs also improves the modelling capability for capturing the characteristics of the distributed generation. Unlike the simplified ADMD models in common use, the more detailed load simulations will allow DNOs not only to identify whether or not localised problems are likely to occur but also to assess how long, how often and under what circumstances.

To provide this risk-based view, the models are required to simulate realistic point loads for each minute over a given time span. Libraries of daily profiles tend to provide loads averaged over groups or over a period of time and are thus smoother than those for an individual consumer or single day. The time series based techniques or those that provide a random element to introduce a range of possible loadings for each consumer or every day, such as McQueen's residential model, or those that are simulated on a bottom-up basis are a considerable improvement.

2.7.3 Using a bottom-up approach

Using an end-use basis for load models, provides the user with a recognisable framework, which extends the possible applications of the models as well as describing both components of the total load. By providing a clear methodological basis for the model, it is feasible to adjust the models to take account of changes in appliances, demographics or lifestyles that affect the demand. Identifiable modules, layers, objects and associations between them also make the models easier to code and manipulate within software packages.

Such requirements tend to rule out models that are based around time series approaches or the black-box models of neural networks. Those that deal with the total load, such as McQueen's, are also excluded (although given the necessary data, the approach used for the total load could of course be applied for end-use demands). These requirements favour the more detailed simulations that account for occupant behaviour or the per building models of the ESP-r tool.

2.7.4 Suitability for urban LV networks

A single LV feeder from an urban primary sub-station can serve hundreds of consumers. Not only must the network loading strategy provide realistic demands but it must also be feasible to use the models for batch processing. The models developed within this research aim to provide the appropriate compromise between accuracy and ease of processing.

Inner city LV networks serve a mix of domestic and non-domestic consumers. Whilst the various energy models described earlier venture into the realms of non-domestic energy consumption, the provision for representing non-domestic electrical demand is relatively sparse. For most purposes at best these are available as continuous hourly load series from databanks (usually in Canada or the USA) or as typical half-hourly, seasonally averaged daily load profiles.

Since the LRG data has been the starting point for the current models, much of the focus for this research has again been on the domestic consumers. However, Chapter 7 will illustrate how the domestic models might be extended to cover smaller non-domestic consumers, albeit with less reliability.

2.7.5 Ease of use

Both Gadsden, in his work to develop the BREDEM-8 models for improved ease of use [Gadsden, 2001], and Walker, in deriving his detailed residential load model [Walker, 1982], acknowledged the problems of gathering sufficient data. Gadsden especially designed his models around the concept of using readily available data at a national level as defaults with the facility to operate with a more complete dataset as available. This concept is important, especially if the models are to be adopted and used in industry. The current research aims to provide models that require the minimum of inputs.

2.8 Summary: Chapter 2

The design and operation of an LV network, especially with small scale embedded generation, requires a detailed understanding of the loading - temporally, spatially and in terms of end-use. In this chapter, many of the techniques adopted for loading networks have been reviewed and their incorporation into the more commonly used tools examined.

No 'off-the-shelf' solutions were found to fit the requirements introduced in Chapter 1. This research therefore seeks to provide DNOs and energy researchers with a means to synthesise realistic network loading data, suitable for use in the UK. Unlike the models currently available, it aims to provide 1-minute averaged demands, calculated per consumer on an end-use basis using default values for factors that affect demand where real data are not available.

Such a detailed and more realistic model, when used in conjunction with load flow analysis, could allow DNOs to take a view on the probability of problems arising within the LV network (notably over-voltages and hot-spots) and their likely locations. Providing a more detailed distribution of loading (in space -per consumer and time – 1-minute averaging) of networks could permit a better simulation of operating conditions when embedded generators are applied to the LV network. Greater confidence can help to diminish the perceived risks and encourage wider acceptance of RETs. The load models, which are described in chapters 3-6, are aimed at providing a realistic distribution of network loading before the application of building-integrated embedded generation (complementary models for PV and solar-thermal output and their consequences on the loading have been developed and are described in Appendix G).

The starting point for the new models has been the LRG half-hourly data for domestic consumers, broken down by end-use for a complete year and as group averaged demands (previously used for the ADMD values that are so widely applied by the UK DNOs). The next chapter explains the conceptual approach that has been adopted.

Chapter

3

Model Concepts

The whole is simpler than the sum of its parts.
WILLARD GIBBS

The process of design has always to take account of the materials and resources available. To create models that synthesise the loading of LV networks, the LRG half-hourly dataset becomes the starting point. This provides values averaged over a group of domestic consumers for one year. As the only raw data available, the nature of this dataset impacted significantly on the direction of the research. Part of the challenge has been to find ways of simplifying the original data, by identifying underlying patterns, and to recreate something of the diversity between the individual consumers.

One of the main aims in designing the load models has been to build a clear and homogenous framework that applies evenly across each of the end-use modules. Employing varying degrees of breadth and depth can distort the simulation and realism of the results. Adopting different techniques for modelling the various end-uses could create a complicated structure which would be difficult to extend or modify. The domestic load model adopts a three-layered approach (Figure 3-1). This chapter looks in more detail at these generalised concepts for the domestic model.

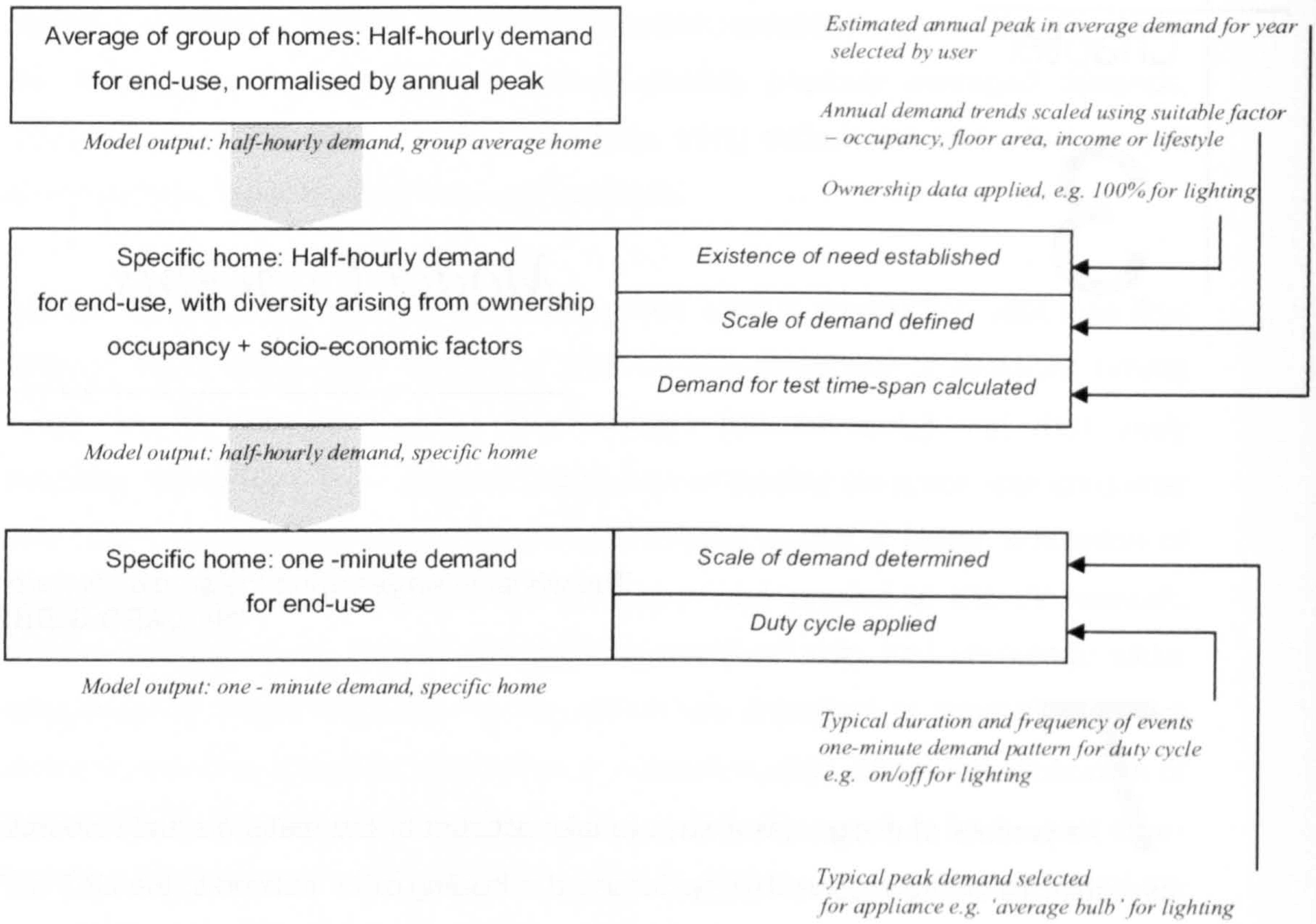


Figure 3-1: Conceptual scheme for domestic load model showing three layered approach

3.1 Layer 1: Half-hourly demand, group average

3.1.1 LRG Dataset

The LRG dataset contained half-hourly demands (in kW) for a group of UK homes over a twelve month period. The total demands were monitored in every house in the survey , located across the UK, from the Shetlands Isles to the Isle of Wight (an integrated database of 1200 homes). End-use data was provided from a variety of projects, originally started in 1992 for nine different types of appliance with additional data for storage and water heating investigated from 1996. An in-depth lighting project was begun in 1996/7. A total of 175 individual appliances were monitored with sample sizes between 22-120 for each category. Consequently the sample sizes and test dates are not consistent for all the end-uses. During the LRG surveys, consumers completed questionnaires regarding their socio-economic description and the number of occupants, type of dwelling, etc. Neither this nor the complete description of the sample sizes were provided with the demand values.

The LRG dataset was used originally to provide seasonally averaged half-hourly profiles, for three day types and two tariffs. The profiles have been applied for trading purposes in the UK, varied by local ambient temperature and sunset timing. The LRG profiles are designed to be accurate to within +/- 2% for financial purposes, when used over a complete year. For trading purposes, the half-hourly aggregated demand is monitored in each half-hour at the Grid Supply Points (GSP). These measured values include the assigned LRG profiled demand, half-hourly metered values, line losses and unmetered supplies (mainly street lighting). The estimates are then scaled to match the measured values. Between July 2001 – June 2002, the scaling factors were within 0.9 -1.1 for almost the entire year [Electricity Association, 2002]. Within this context, the LRG load profiles and underlying data are demonstrated to be very accurate when viewed on a highly aggregated basis.

For the samples of data for the 1996/7 period, the averaged consumption for all uses was stated to be around 15% above the comparable national figure [Electricity Association, 1998(b)], believed to arise from slightly above average income levels and higher appliance ownership of dishwashers and electric cookers. The implications for the load model research are these:

- the total demand may be slightly higher than in the average UK home (up to 15% of the annual mean value)
- the end-use demands, notably for cooking and dishwashers, could be higher than for the average UK home (less than 15% of the annual mean)
- the estimates of miscellaneous demand (which is based on the difference between the total and summations of the other end-uses, described further in section 4.7) may be distorted by the patterns of demand for cooking and dishwashers

In short, the load models are inevitably likely to be more valid for dwellings that are similar to the original LRG dataset – marginally wealthier and with higher appliance use – than the national average. As described later (Section 3.3), the assigned demand is eventually used as a probability to trigger specific demand events. The eventual scale of demand is defined by use of appliance ratings, based on levels for currently available units (Section 3.3.2). However, the frequency with which an event is triggered (Section 3.3.4) can be higher than is realistic. The problems associated with the higher demands in the LRG datasets are to some extent mitigated by the comparison of the frequency with which events are triggered against measured data (notably from Mansouri et al's study [Mansouri et al, 1996] and consequent re-calibration of the model to suit.

A further concern regarding the available datasets was the potentially small sample sizes, known to be low for space and water heating demands and, based on the peakiness of the averaged data, possibly also for dishwasher and shower demands. A spiky characteristic for the group averaged demands can arise from low diversity (i.e. several homes with the same end-use within the same half-hour) or from a small sample size. It was not possible from the available information to determine which was the case. The implications for the model, which are discussed in more detail in the sections that follow, are that, for these categories of end-use, it is hard to identify the underlying patterns of use and hence model them appropriately. This was a significant problem for analysis of demand for the use of showers and prevented the construction of a separate module within the model for these appliances.

For most domestic consumers, electricity is supplied on the basis of two tariffs. The unrestricted tariff has a flat rate charge for electricity used at any time of the day. Off-peak tariffs encourage use of electricity in the home during periods when demand from most consumers is low and was introduced to even the daily loading. A lower charge rate applies during seven off-peak hours, typically between 23:00 and 06:00 (although these times may vary between regions), giving rise to the tariff being labelled Economy-7. For some of the end-uses (those which are more likely to be scheduled to take advantage of off-peak rates), data were measured for unrestricted and Economy-7 tariffs. Table 3-1 summarises the contents of the LRG dataset.

Description of demand	Time span for data collection	Tariffs (where defined)		Number of homes in sample (where known)
		Un-restricted	E7 (off-peak)	
Total	April 1996 – March 1997	X	X	175
Lighting[1] *(fixed and portable lighting)*	April 1996 – March 1997	combined		100
Space heating *(storage heaters)*	January 1996 – December 1996 & April 1999 – March 2000		X	22
Water heating *(immersion heaters)*	August 1996 – July 1997 & April 1999 – March 2000	X	X	16 – Unrestricted 22 – Economy 7
Cooling: *Refrigerators 'Fridge-freezers Freezers*	January 1996 – December 1996	combined		*
Cooking *(assumed hob and oven combined)*	January 1996 – December 1996	combined		*
Wet appliances *Washing machine Tumble dryer Dishwasher*	January 1996 – December 1996	X	X	*
Shower	January 1996 – December 1996	combined		*

* thought to be between 20-120

Table 3-1: Summary of LRG domestic dataset

3.1.2 Normalising the data

The LRG end-use data covered different 12 monthly periods depending on end-use. Additionally, since the model was intended to cover future as well as current situations, the first step was to create a pattern of demand that could be adjusted by long term trends. The end-use/appliance data are normalised by dividing the measured values by the peak demand that occurs in each set (Equation 3-1).

$$D_{model\_n} = D_{measured\_n} / D_{max\_n} \qquad \textbf{[3-1]}$$

where, for the n^{th} end-use:

D_{model_n} is the demand dataset used for the model (kW)

$D_{measured\_n}$ is the half-hourly averaged dataset measured by the LRG (kW)

D_{max_n} is the annual peak demand value recorded (kW, for each tariff if applicable)

[1] Lighting data were available for Scotland and northern and southern England

The peak rather than the average demand was chosen since this value is easily found; use of peak demand values is common in the electricity industry (the peak value can arise from exceptional circumstances whilst the average is less sensitive; however, the peak demand in this case has already been averaged over a group of consumers). From this point on, the model assumes that the pattern of demand in the 12 months over which the measurements were taken is typical of the pattern in future years, such that the relationship between the peak and average demands in all years are the same.

3.1.3 Underlying patterns in diversified half-hourly demand

A typical daily profile of the total demand tends to be characterised by two peaks (Figure 3-2).

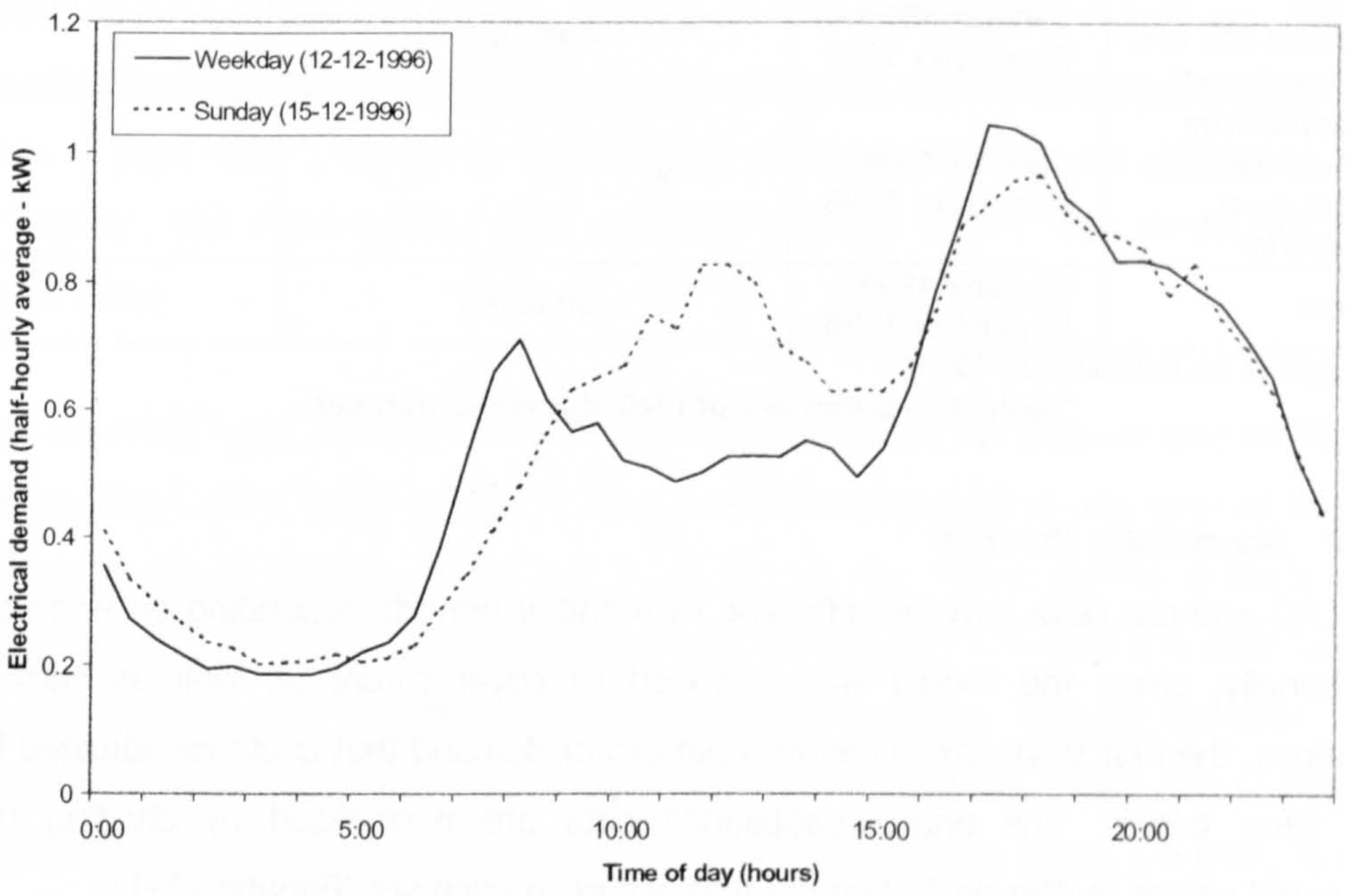


Figure 3-2: Typical daily profile of total demand - group average, half-hourly demand (winter weekday, unrestricted tariff)

Occupant behaviour influences the shape of the daily profile considerably, with the peaks representing activity around breakfast time and during the evening. Demand dips at night and during the day, when there is generally less activity in the home. The pattern of demand is also very different at weekends compared to weekdays, when there is a greater diversity amongst consumers in the morning. Diurnal trends in the ambient temperature affect demand for heating, cooking, cooling and washing. Variations in the availability of natural light and solar irradiation due to sunrise and sunset as well as cloud cover clearly affect lighting demand but also activity levels [Wright, 2004]. It is this combination of the naturally occurring effects and the occupant activity that make daily patterns of demand so difficult to model, causing a highly non-linear relationship with time.

The underlying pattern of demand for each end-use arises from a mixture of these influences. Both occupant behaviour and natural effects incorporate some element of predictability as well as a random component. A number of curve fitting options were investigated to describe the predictable pattern (including simple regression, polynomial, Fourier analysis) but rejected on the basis that they did not provide a simple basis with which the user might identify. For example, the lighting daily demand curve for the LRG data on 21st December, 1996 can be represented by a polynomial with degree 4 (using a MATLAB polynomial fitting routine based on least squared error, Figure 3-3).

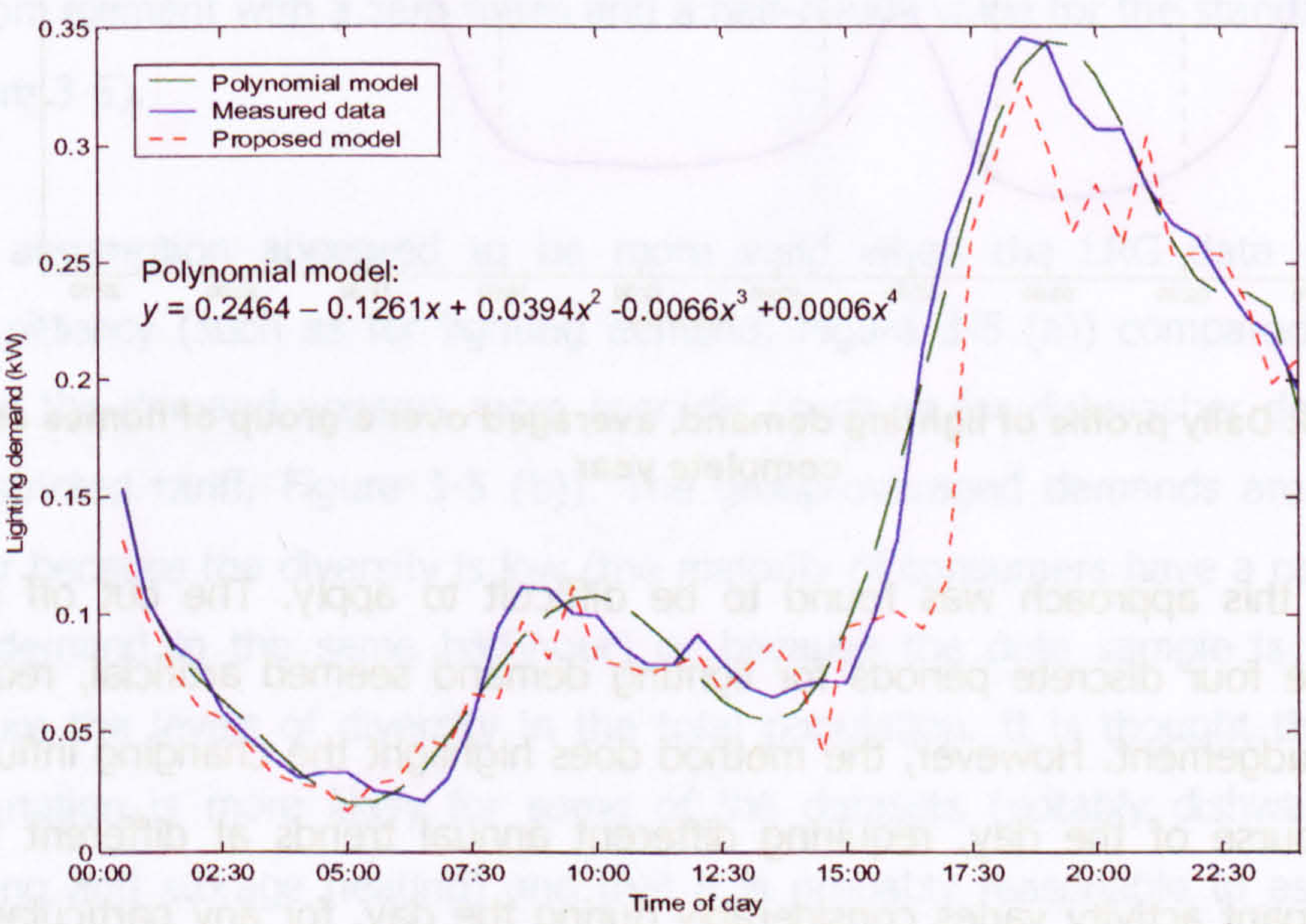


Figure 3-3: Comparison of LRG lighting data for 21st December, 1996 with a polynomial model of demand and that derived from the model described in this research

In the Sustainable Cities project [Halliday et al, 2001], which was based on the same LRG data, the daily demand patterns were split into discrete periods. For example, the lighting demand curves (Figure 3-4) were sectioned into night-time, morning peak, daytime and evening peak demands. Each portion of the profile was modelled by a separate function and annual trends for these functions identified. The morning peak, for example, was modelled by a Gaussian function, described by the peak height, width and timing. The evening peak was described by a function, which included the description of the leading and falling edges. Further relationships were investigated to describe the annual trends for each parameter, e.g. the leading edge parameter of the evening lighting peak was found to have a sinusoidal relationship with respect to day number whilst the trailing edge parameter was constant throughout the year.

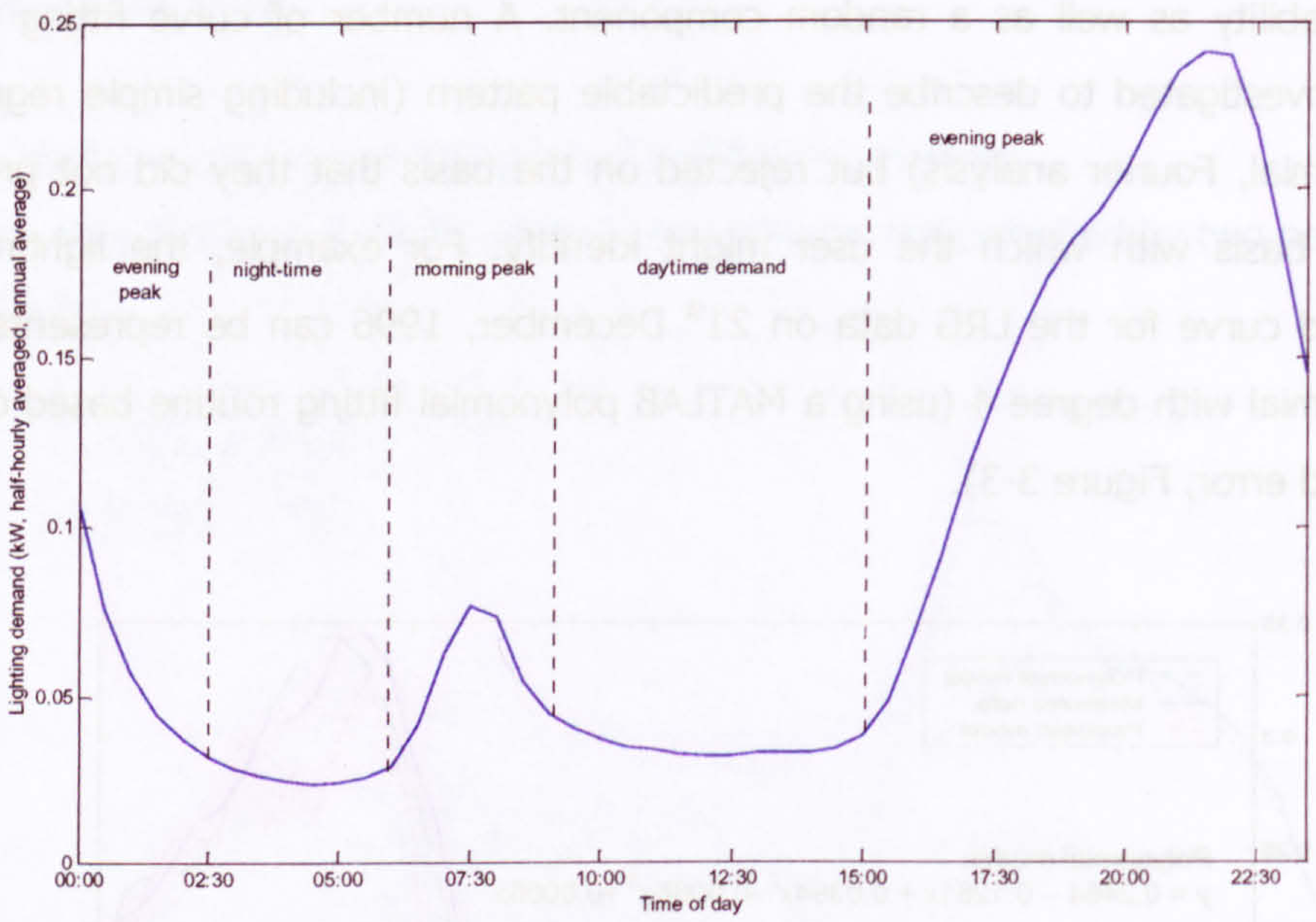


Figure 3-4: Daily profile of lighting demand, averaged over a group of homes and a complete year

In practice this approach was found to be difficult to apply. The cut off points between the four discrete periods for lighting demand seemed artificial, requiring subjective judgement. However, the method does highlight the changing influences over the course of the day, requiring different annual trends at different times. Whilst occupant activity varies considerably during the day, for any particular half-hour it is likely to be relatively constant throughout the year. This is especially true when different day types are considered separately – using sub models for weekdays, Saturdays and Sundays (public holidays can usually be associated with either Saturday or Sunday).Consequently, when the demand for each half-hour of the day is examined on an annual basis, the pattern tends to relate to the effects of the solar cycle – arising from the external ambient temperature, solar irradiation or sunrise and sunset times. These relationships are, for the most part, sinusoidal. Analysis of the LRG data certainly confirmed that this approach was viable.

It was found that the annual trends in the demand data for each half-hour generally resembled a sine curve that could be described by amplitude and phase together with a constant. These varied depending on the type and time of day. In some cases (e.g. lighting), it was also necessary to introduce a minimum term (for times of the year when, generally, natural lighting is available – demand existing mainly for illuminating areas with little or no glazing) and a maximum term (no natural lighting available). The details of each of the end-use models will be described in more depth in the next chapter.

Viewed on an annual basis, the measured demand in each half-hour shows a day to day variation from the underlying sinusoidal trend – arising from changes in temperature, cloud-cover and detailed occupant behaviour. The LRG data on the whole suggested that this variation could be described as a normally distributed random element with a zero mean and a half-hourly value for the standard deviation (Figure 3-5).

This assumption appeared to be more valid when the LRG data showed less intermittency (such as for lighting demand, Figure 3-5 (a)) compared to datasets where the demand appears more sporadic (such as for dishwasher demand on an unrestricted tariff, Figure 3-5 (b)). The group-averaged demands are intermittent either because the diversity is low (the majority of consumers have a particular end-use demand in the same half-hour) or because the data sample is too small to capture the levels of diversity in the total population. It is thought that the latter explanation is more likely for some of the datasets (notably dishwashers, water heating and storage heating) and that it is probably reasonable to assume that a Gaussian random variation might apply for a larger group of consumers.

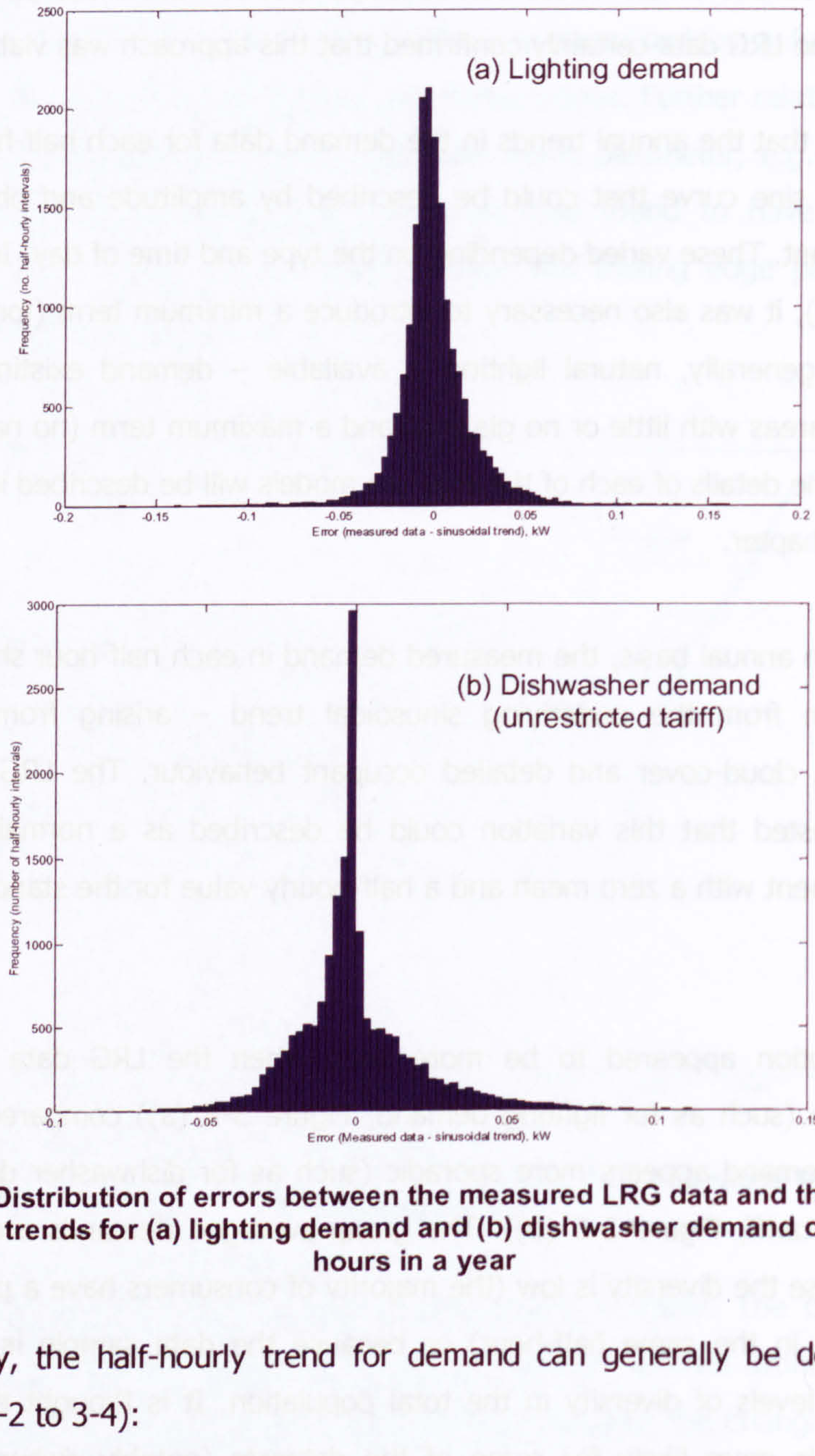


Figure 3-5: Distribution of errors between the measured LRG data and the underlying sinusoidal trends for (a) lighting demand and (b) dishwasher demand over all half-hours in a year

Consequently, the half-hourly trend for demand can generally be described thus (Equations 3-2 to 3-4):

$$D_{sine} = s \times \sin\{(2\pi \times N_d/N_y) - \varphi\} + k + r \qquad \textbf{[3-2]}$$

where:

s = sine amplitude

N_d = day number in a given year

N_y = number of days in a given year

φ = sine phase

k = constant

r = random number from a normal distribution (mean = 0 and standard deviation = σ_{sine})

When a minimum or maximum value applies, then demand is given by :

If $D_{sine} \leq D_{min}$ $\qquad D = D_{min} + r_{min}$ **[3-3]**

If $D_{sine} \geq D_{max}$ $\qquad D = D_{max} + r_{max}$ **[3-4]**

where:

r_{min} and r_{max} are random numbers from normal distributions (mean = 0, standard deviations = σ_{min} and σ_{max})

Consequently, the demand, D, is either given by D_{sine}, D_{min} or D_{max}. The demand for any end-use cannot be a negative value and the calculated value is set to zero if a negative demand arises (equation 3-5):

If D<0 $\qquad$ D = 0 **[3-5]**

Thus the annual pattern of demand for a given end-use or appliance may be stored for different tariff types and day types as a database of values using some or all of the following variables:

- Sine amplitude
- Sine phase
- Sine constant
- Sine standard deviation
- Minimum value
- Minimum standard deviation
- Maximum value
- Maximum standard deviation

These values are stored for each half-hour. They are derived from the LRG data by minimising the difference between the sum of the square of the 'errors' between the basic trend curve (i.e. the sinusoidal curves, without the random component added) and the measured data ('least squares' method). The values for the standard deviation for the random elements were calculated for the relevant part of the 'error'. (Figure 3-6 illustrates the combination of components that describe the modelled demand for storage heating during the half-hour 01:00-01:30).

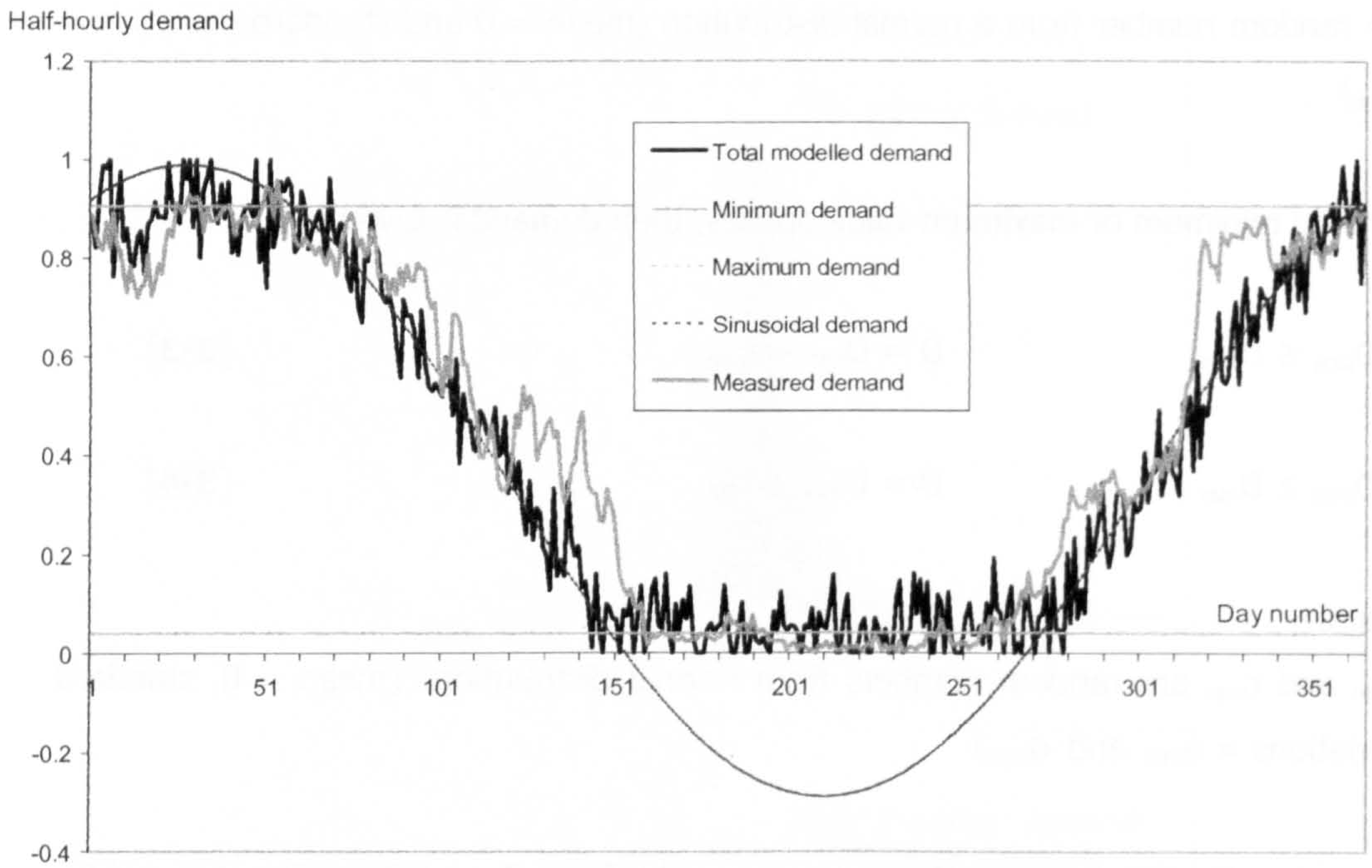


Figure 3-6: Storage heating demand during 01:00-01:30 (normalised by the annual peak demand) showing the components used to model demand and compared to the measured data.

Since the LRG data already accounts for influences due to the temperature, daylight availability and weather (modelled as part of the daily and annual trends as well as a random factor), the model does not use data from a 'weather engine' as an input. Within the model, there is no link between the random component in the demand for one end-use and another as there might be in practice – a particularly cold wet day might create high demands for all end-uses bar cooling. There is also no connection between the random elements from one half-hour to another as may occur in reality – cloud cover might occur throughout the day influencing demand for lighting similarly during consecutive half-hours.

The aim of the model is not to provide highly accurate forecasts of the peak demand nor the aggregated annual energy demand for groups of consumers (although chapter 4 indicates that the model can provide reasonable estimates); this would require more sophisticated approaches, such as those adopted by the Tesla model [Tesla, 2000]. Such precision has been sacrificed to simplicity, allowing a bottom-up approach to be adopted for several hundred consumers. The purpose of this layer of the model is to provide a realistic simulation of individual demands, which are applied later as a probability that a particular appliance is in use. Limitations of the complete model are explored further in Chapter 8.

3.1.4 Long-term trends

The long-term trends in demand are not always increasing; this is dependent on end-use. For example, the demand for lighting rose by over 10% between 1990 and 2000 (driven largely by trends towards increased portable lighting, Figure 3-7). In the same period, demand from electric hobs and ovens decreased by 23% (improved unit efficiencies as well as more 'ready meals' being warmed in microwave ovens). Data from the Market Transformation Programme (MTP) [DEFRA, 2001] provided the basis for the trends in each of the end-uses.

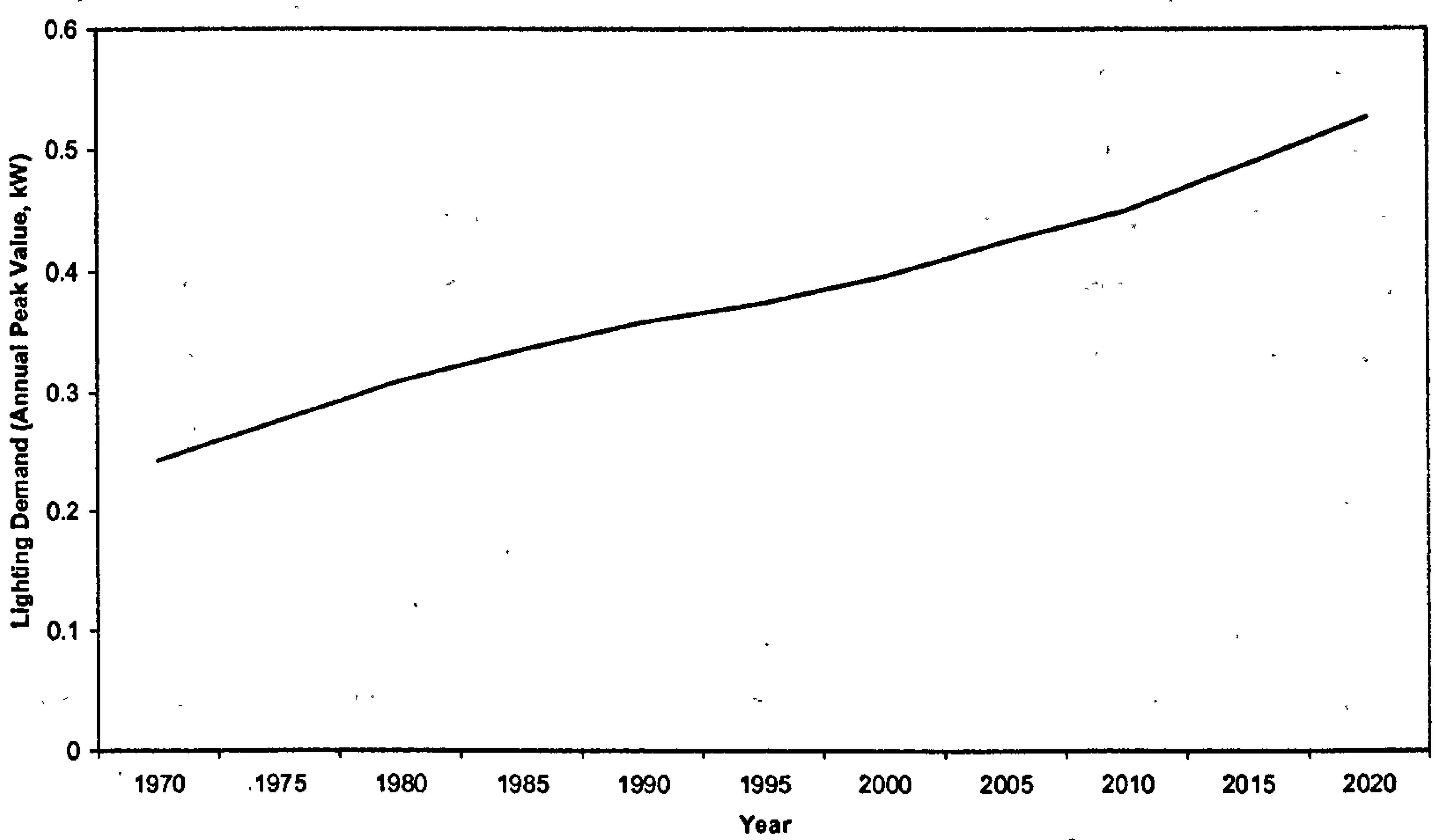


Figure 3-7: Long term trends in lighting demand for the domestic group average

For the purposes of the domestic load model, it is assumed that this long-term trend in energy use is the same for the peak in the diversified annual power demand. Consequently, the normalised patterns of demand, simulated by layer 1, are scaled by the predicted value of the annual peak (Equation 3-6).

$$D_{HHgroup\_n} = D_n \times D_{max\_trend\_n} \qquad [3\text{-}6]$$

where, for the n^{th} end-use:

$D_{HHgroup\_n}$ is the annual set of half-hourly demands estimated by the model for a group of domestic consumers (kW)

D_n is the set of modelled annual patterns in each half-hour

$D_{max\_trend\_n}$ is the annual demand peak estimated by the trends (kW)

3.2 Layer 2: Half-hourly averaged demand – specific home

3.2.1 Ownership

The next step begins to introduce some elements of diversity of which the most important is ownership. Clearly not all homes have a requirement for every end-use – for example less than 10% of UK homes use electricity for space heating [DEFRA, 2001]. Collecting data for detailed ownership is likely to be beyond the means of many users and the model is designed to use national statistics as a default, with the facility to use regional, local or specific ownership levels as available. Unless specifically known, ownership is applied on a random basis. In some cases, the assignment of demand is rule-based – for example, linked ownership of one appliance with another. A variety of sources were used to identify typical ownership levels, associated rues and future trends [DEFRA,2001; Mansouri et al, 1996; Boardman et al, 1994].

3.2.2 Occupancy

In a specific home, once an end-use demand has been assigned, the next aspect of diversity arises from factors that influence the scale of demand. The number of occupants in a home has a significant effect – since many appliances are sized accordingly and higher occupancy generally increases the chance that an appliance will be used. In most cases, there is a fixed component (the level of demand for a single occupant) and a variable element (usually a linear relationship with additional occupants). For many end-uses the demand level tends to remain constant when four or more people share a dwelling. The DECADE research provided the basis for a number of relationships between the scale of demand and the number of occupants [Boardman et al, 1994]. Data regarding occupancy can also be hard to obtain and the standard occupancy calculation of BREDEM-8 [Shorrock et al, 1991] is adopted for the model in order to relate occupancy to floor area (Equations 3-7 and 3-8).

$$N = 0.0365 \times TFA - 0.00004145 \times TFA^2 \quad \text{for } TFA <= 450\ m^2 \quad [3\text{-}7]$$

$$N = 9 / (1 + (54.3/TFA)) \quad \text{for } TFA > 450\ m^2 \quad [3\text{-}8]$$

where:
N is the number of occupants
TFA is the total floor area (m^2)

Floor-area may be estimated from GIS maps (for example, using a novel footprint tool [Rylatt et al, 2003] or the Ordnance Survey MasterMap™ polygons [Curtis & Painter, 2001]). The average occupancy is assumed to be 2.4 people [National Statistics, 2001(a)]. An occupancy scaling factor is applied to the group averaged demand (output from layer 1 of the model) to assign a specific half-hourly demand pattern to each connection point, tending to reduce demand for one or two occupants and increasing demand for three or more.

3.2.3 Income and socio-economic factors

In some cases, such as lighting, relationships have been studied between demand and income or lifestyle index [Electricity Association, 1998(b)]. These relationships alter not only the overall scale of demand but also the daily demand pattern. Using these relationships, the half-hourly pattern is adjusted by scaling annual trends in each half-hour.

Income factors are applied in relation to the national average income per household (above, average or below national average - £25,000 in 2001/2 [National Statistics, 2001(b)]). Lifestyle index is based on the new ACORN[2] ratings (A to F) which are explained further in Chapter 5 (these are widely available at the post-code level [UpMyStreet™,2003]). Within the model, such factors are only used to adjust lighting and miscellaneous demand and random assignment of ownership. Since the two factors are interrelated, income, if known, is used in preference to lifestyle factor. Alternatively, the lifestyle factor (randomly assigned, if unknown) is applied.

[2] The ACORN system is a socio/economic/demographic system for classifying different categories of households. The profiles were updated in 2000 to reflect lifestyle changes and there are now 56 different categories that provide information on occupant numbers, income, ambitions and demographics [CACI, 2004]

3.2.4 Other elements of diversity

Further elements of diversity exist between consumers, such as the detailed effects of the building fabric, orientation, location, position and area of glazing and the behavioural factors associated with the occupants. The data for these features can only be gathered by a detailed site survey and they were considered to be outside the scope of this research. The model is designed for flexibility and further elements of scaling or adjustment of the annual demand patterns may be introduced as required. For example, occupancy profiles may be incorporated (e.g. the absence of students in university accommodation during vacations or of workers during weekdays). Demand patterns can be reduced or increased during certain times of the day or year. This extra layer of scaling is in fact used to apply demand trends from the domestic model for use with non-domestic consumers (described further in chapter 7).

3.2.5 Output from layer 2

Layer 2 of the model provides a half-hourly demand pattern (in kW), incorporating the major elements of diversity, for a specific domestic consumer for any of the required end-uses (Equation 3-9)

$$D_{HHspecific\_n}(i,j) = D_{HHgroup\_n}(i,j) \times k_{own\_n} \times k_{occ\_n} \times k_{econ\_n}(j) \qquad \textbf{[3-9]}$$

where, for the n^{th} end-use:

$D_{HHspecific\_n}(i,j)$ is the half-hourly demand in the j^{th} half-hour on the i^{th} day

$D_{HHgroup\_n}(i,j)$ is the group-averaged half-hourly demand (Equation 3-6)

k_{own_n} is a Boolean factor (= 0 if end-use not assigned, = 1 if end-use is assigned)

k_{occ_n} is a scaling factor depending on occupancy

$k_{econ\_n}(j)$ is an economic scaling factor in the j^{th} half-hour of the day that relates either to income or lifestyle factor

Homes with the same floor area (or occupancy), appliance ownership and socio-economic factors will be assigned the same pattern of half-hourly demand. The final layer of the domestic model uses this assignment to trigger appliance duty cycles on a random basis, as explained in the next section.

3.3 Layer 3: 1-minute demand for a specific home

3.3.1 Characteristics of appliance duty cycles

The same assignment in layer 2 creates different patterns of 1-minute demands in layer 3 which introduces significantly more diversity between consumers. Each connection point is likely to have a unique modelled daily demand (Figure 3-8).

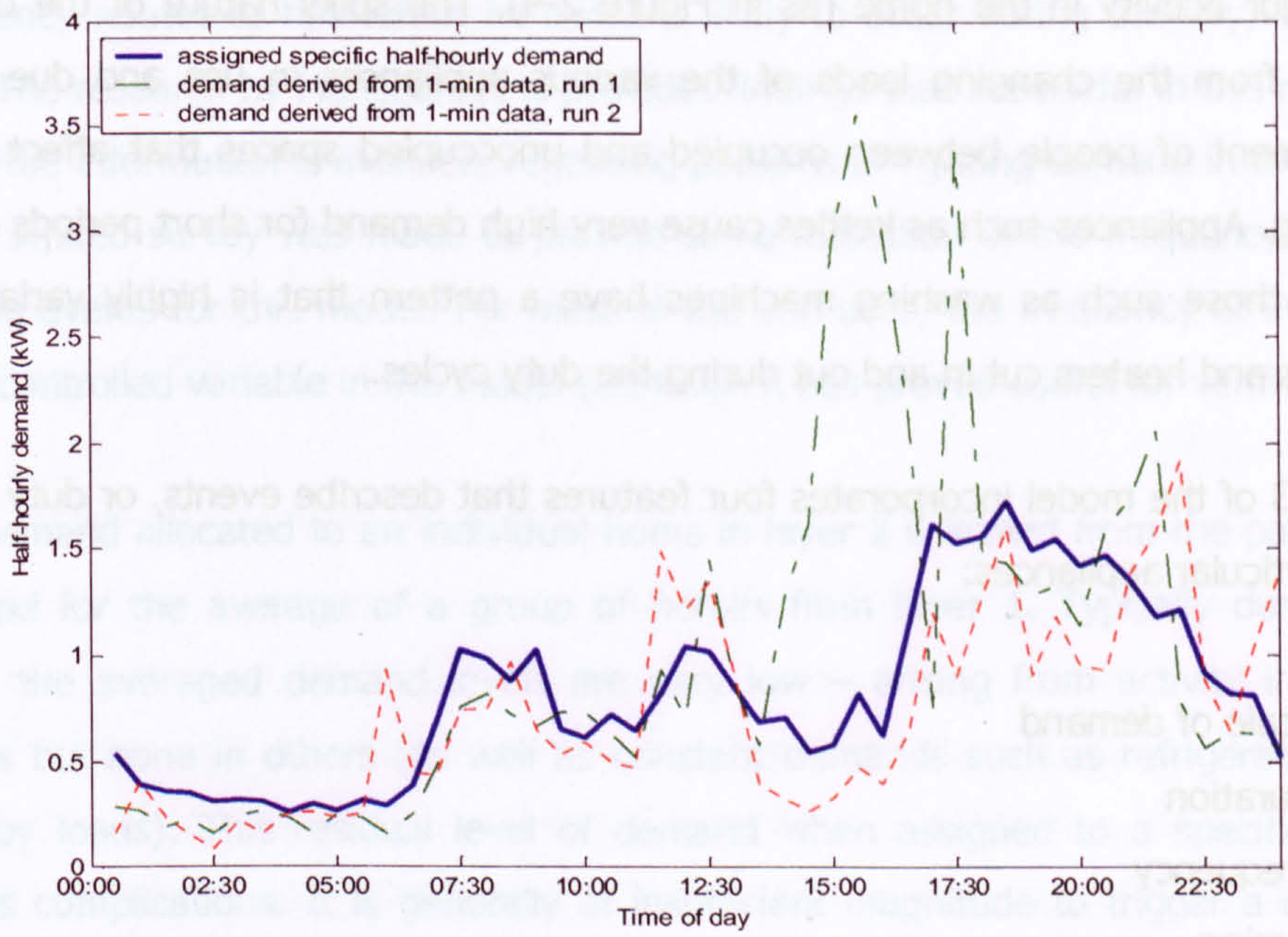


Figure 3-8: Graph showing the variation in two half-hourly demands derived from the 1-minute demand simulations, compared with the original assigned demand (4-person high income home, March weekday)

The difference between run 1 and run 2 arises simply from the random triggering of uses of appliances. Several coincident events, with a high level of demand, are triggered in run 1 compared to run 2 (Section 5.9 and Figure 5-10 explore this variation in greater depth). Layer 3 of the model allows for significantly increased diversity in the level of demand from one consumer to another (or on one day to the next for the same consumer) whilst maintaining a group averaged demand that is similar to the national average (and this will clearly depend on how the group concerned compares to national statistics in terms of the scaling factors discussed in the previous section).

Demand averaged in any half-hour may arise between one extreme, with a constant load over the whole period, to the other - a short burst of demand at high level. There were no 1-minute averaged end-use demand datasets available for this research and consequently, the challenge for the model at this layer has been to synthesise a realistic pattern that is consistent with typical appliance characteristics.

Domestic demand averaged over 1-minute changes rapidly, especially during times of major activity in the home (as in Figure 2-4). The spiky nature of the demand arises from the changing loads of the various appliances in use and due to the movement of people between occupied and unoccupied spaces that affect use of lighting. Appliances such as kettles cause very high demand for short periods of time whilst those such as washing machines have a pattern that is highly variable, as motors and heaters cut in and out during the duty cycles.

Layer 3 of the model incorporates four features that describe events, or duty cycles, for particular appliances:

- Scale of demand
- Duration
- Frequency
- Timing

3.3.2 Scale of an appliance event

The scale of demand relates to typical appliance ratings. For many of the end-uses, a brief survey of rated demand for appliances currently available in retail outlets established the range. The DECADE research [Boardman et al, 1994] provides some indication to relate the manufacturers published ratings against demand levels measured during tests – which are sometimes under-quoted. Other sources were also used to determine typical variations in demand during an appliance event [Newborough & Augood, 1999; DEFRA, 2001]. In some cases a typical level of demand is used (e.g. lighting events based on 'average' bulbs), sometimes varied randomly for different consumers. For others the model adopts typical duty cycles.

3.3.3 Duration of an appliance event

The duration of an event is either set between random limits (e.g. a kettle event between 2-5 minutes) or is related to observed appliance duty cycles (e.g. a wash cycle). As before, information from Boardman et al, Newborough and Augood, the MTP and Mansouri et al [Mansouri et al, 1996] provide the basis to define duration of events for several appliances. Where data could not be gleaned from existing research, observations were made of event durations, which were timed during limited surveys (single house, one week or one cycle).

3.3.4 Frequency of appliance events

Frequency relates to how often an event is likely to occur during the day, week or year. The research by Mansouri et al provides findings that are useful in this respect. Very little information is available regarding patterns of lighting demand in the home and a limited survey was made to provide some indication of the frequency of new lighting events for this model. For most of the end-uses, the frequency of events is not a controlled variable in the model (although it has proved useful for verification).

The demand allocated to an individual home in layer 2 is scaled from the pattern of demand for the average of a group of homes from layer 1. Typically during the night, the averaged demand levels are very low – arising from activity in a few homes but none in others (as well as constant demands such as refrigeration and standby loads). This residual level of demand when assigned to a specific home causes complications. It is generally of insufficient magnitude to trigger a demand event for any of the appliances related to an end-use. The model must adopt strategies that allow events to be triggered in some homes even when the assigned half-hourly demand is insufficient. The strategy used for most of the end-uses is to create a probability that an event occurs, such that when the allocated half-hourly demand is low the probability is also low.

Once the scale and duration of an event are set, the demand, averaged over a half-hour (for events lasting more than 30 minutes, the demand in the first half-hour is used) can be compared against the half-hourly demand allocated to the specific house. A random number is generated and if less than or equal to this ratio, an event is triggered (Equation 3-10 to 3-12)

$$\text{Pr (event occurring)} = D_{HHspecific\_n}(i,j) \;/\; D_{HH\_appliance\_n} \qquad \textbf{[3-10]}$$

if $R \leq Pr$, event is triggered

$$D_{min\_n}(i,k) = D_{min\_appliance\_n}(k) \qquad [3\text{-}11]$$

if R > Pr, event is not triggered

$$D_{min\_n}(i,(((j-1)*30)+1):(j*30)) = 0 \qquad [3\text{-}12]$$

where, for the n^{th} appliance/end-use:

Pr is the probability of an event occurring in the j^{th} half-hour on the i^{th} day

R is a random number , $0 \leq R \leq 1$

$D_{HHappliance\_n}$ is the typical half-hourly demand (kW)

$D_{HHspecific\_n}(i,j)$ is the assigned half-hourly demand (Equation 3-9)

$D_{min\_n}(i,k)$ is the 1-minute demand (kW) for the i^{th} day and the k^{th} minute

$D_{min\_appliance\_n}(k)$ is the 1-minute demand (kW) that arises from the assigned duty cycle, duration and start time. It may have any value from 0 to the 1-minute peak demand (kW)

D_{min_n} is the matrix of demands on the i^{th} day, setting the demand for each minute of the jth half-hour (zero when no event occurs)

For some end-uses, multiple events are allowed to occur simultaneously (e.g. lighting events) whilst for others they are not (e.g. wash events). For the former case, the half-hourly averaged demand used by each event is subtracted from the allocated demand and the remainder used to determine the probability of a further event. This forms the generalised basis for the 1-minute demand model. Chapter 6 provides more information for each end-use.

3.3.5 Timing of an appliance event

The timing of a demand event relates to when it begins and, in association with the duration, when it ends. For most end-uses, appliance events are triggered randomly to start at any time within the half-hour. Events frequently role over into consecutive half-hours and the demand allocated may be reduced accordingly.

3.4 Description of the total load

3.4.1 Reactive component

As described in Chapter 1, there are two components of the total load – the active and reactive components. Looking at the active component alone can cause a significant underestimate of the current flowing through the networks. Loads with power factors of 0.7 create 43% more current than for a unity power factor. Effectively, the reactive component of the load wastes energy. Maximising the power factor has the same effect as reducing the line loss, decreasing the required levels of generation and hence greenhouse gas emissions for the same useful (active) component of the demand. It is highly desirable to operate networks as close to a unity power factor, and hence zero reactive load, as possible. Non-domestic consumers who are metered have an economic incentive to manage the power factor since the cost of supply is related to a fused maximum demand that is agreed between consumers and suppliers. Power factor correction equipment is frequently installed and savings of 20% on electricity costs by such means are not uncommon. Price control arrangements for distribution and supply to be introduced in April 2005, require the DNOs to include charges for low power factors for larger consumers [DTI, 2004].

The load models therefore define the power factor at the 1-minute level such that, when used within load flow analysis packages, it is possible to monitor the current flowing more closely and therefore predict the probability and durations of over-heating events and to identify their likely locations. In the preceding discussion, thus far, the three layers of the model provide the active component of the demand, for each day of the selected period (where N_{span} is the total number of days), for each of the end uses:

- diversified half-hourly demand, $D_{HH\_group\_n}(1{:}\ N_{span},1{:}48)$ from layer 1
- specific half-hourly demand, $D_{HHspecific\_n}(1{:}\ N_{span},1{:}48)$ from layer 2
- specific 1-minute demand levels, $D_{min\_n}(1{:}\ N_{span},1{:}1440)$ from layer 3

A value for the power factor is associated with each end-use, which depends on the nature of the associated appliances (in some cases, the influence of component parts of the appliances during the duty cycle, e.g. during the wash cycle a power factor of 1.0 is used as load arises from the heating elements but 0.9 when it is due to the spin motor). The reactive component of the demand is calculated from the power factor (Equations 3-13 and 3-14).

$$D_{reactive\_n} = D_{active\_n} \times \tan(\varphi_n) \qquad \textbf{[3-13]}$$

$$\varphi_n = \cos^{-1}(PF_n) \qquad \textbf{[3-14]}$$

where:

$D_{reactive\_n}$ is the reactive component of the demand

D_{active_n} is the active component of the demand

(given by $D_{HH\_group\_n}(1:N_{days},1:48)$, $D_{HHspecific\_n}(1:N_{days},1:48)$ or $D_{min\_n}(1:N_{days},1:1440)$)

φ_n is the phase angle (degrees) $90^\circ \leq \varphi_n \leq -90^\circ$

3.4.2 Total loads

The total active and reactive loads are found by summing the demands for all the end-uses (Equations 3-15 and 3-16)

$$D_{total\_active} = \Sigma_1^n D_{active\_n} \quad \textbf{[3-15]}$$

$$D_{total\_reactive} = \Sigma_1^n D_{reactive\_n} \quad \textbf{[3-16]}$$

where:

D_{total_active} is the matrix of total active loads (in kW)

$D_{total\_reactive}$ is the matrix of total reactive loads (in kVAR)

This provides the model output for use in network load flow analysis software. The total load is simply the vector sum of these two components (Equation 3-17 and 3-18).

$$D_{total}(i,t) = \sqrt{(D_{total\_active}(i,t)^2 + D_{total\_reactive}(i,t)^2)} \quad \textbf{[3-17]}$$

$$\varphi_{total}(i,t) = \tan^{-1}(D_{total\_reactive}(i,t)/D_{total\_active}(i,t)) \quad \textbf{[3-18]}$$

where:

$D_{total}(i,t)$ is the total load (kVA) on the i^{th} day and t^{th} time interval (half-hourly or per minute)

$D_{total\_active}(i,t)$ and $D_{total\_reactive}(i,t)$ are the active and reactive loads for the same day and time interval

$\varphi_{total}(i,t)$ is the phase angle of the total load

3.5 Summary : Chapter 3

This completes the outline of the concepts underlying the domestic model design. In summary, layer 1 models the LRG datasets, providing a group-averaged half-hourly demand. This layer of the model is based on sinusoidal relationships with respect to day number, resulting in a basic annual pattern of demand. A Gaussian random element is also incorporated. The parameters for these relationships are derived directly from the LRG data. This pattern is scaled to provide for long-term trends in the various end-use demands.

For layer 2, the half-hourly demand is varied for specific consumers, by scaling the underlying annual patterns. The number of occupants in a house, estimated from the floor area, household income and socio-economic classifications are used to provide these scaling factors.

Finally, in layer 3, the assigned half-hourly demand is applied as a probability that an appliance use event takes place in order to derive the 1-minute average demands which are unique to each consumer. These demands are based on typical appliance duty cycles.

The next three chapters illustrate how this basic design is applied at each layer for different end-uses.

Chapter

4

Domestic Model: Layer 1

(Group, half-hourly demand)

For in and out, above, about, below,
'Tis nothing but a Magic Shadow-show,
Play'd in a Box whose Candle is the Sun,
Round which we Phantom Figures come and go.
OMAR KHAYYAM

The sun provides an underlying framework on which our lives are organised. Demand for lighting is influenced by sunrise and sunset as well as the weather patterns that affect cloud cover. Demand for heating (space, water, washing or cooking) and cooling is affected by various weather features, notably the external ambient temperature. These factors not only have obvious effects on appliance demand but they have a more subtle influence on human activity.

In studying the impact of climate change on electricity demand, the effects of humidity, wind speed, solar insolation and temperature were found to account for 80% of the variation in monthly aggregated electrical demand, with temperature being the most significant [Sailor, 2001]. The broad pattern for each of these climate parameters is an underlying annual sinusoidal trend, together with a random element that is generally assumed to be Gaussian [Allcroft et al, 2002] (Figures 4-1 to 4-5).

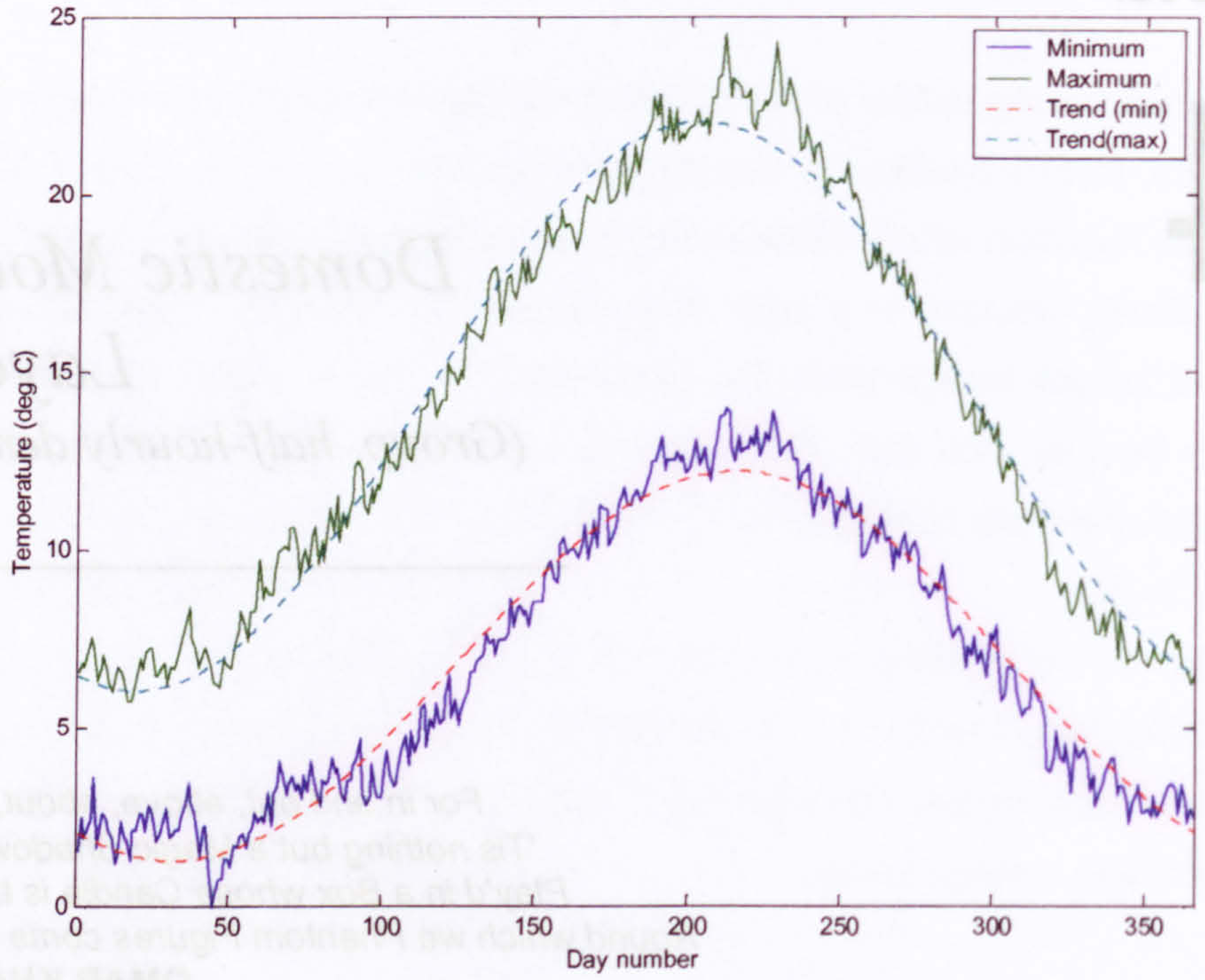


Figure 4-1: Typical annual trends in maximum and minimum external temperatures (mean values over 1973-2002, at latitude 52° 03'N, 0° 0'W, 78m above sea level [Barker,2004])

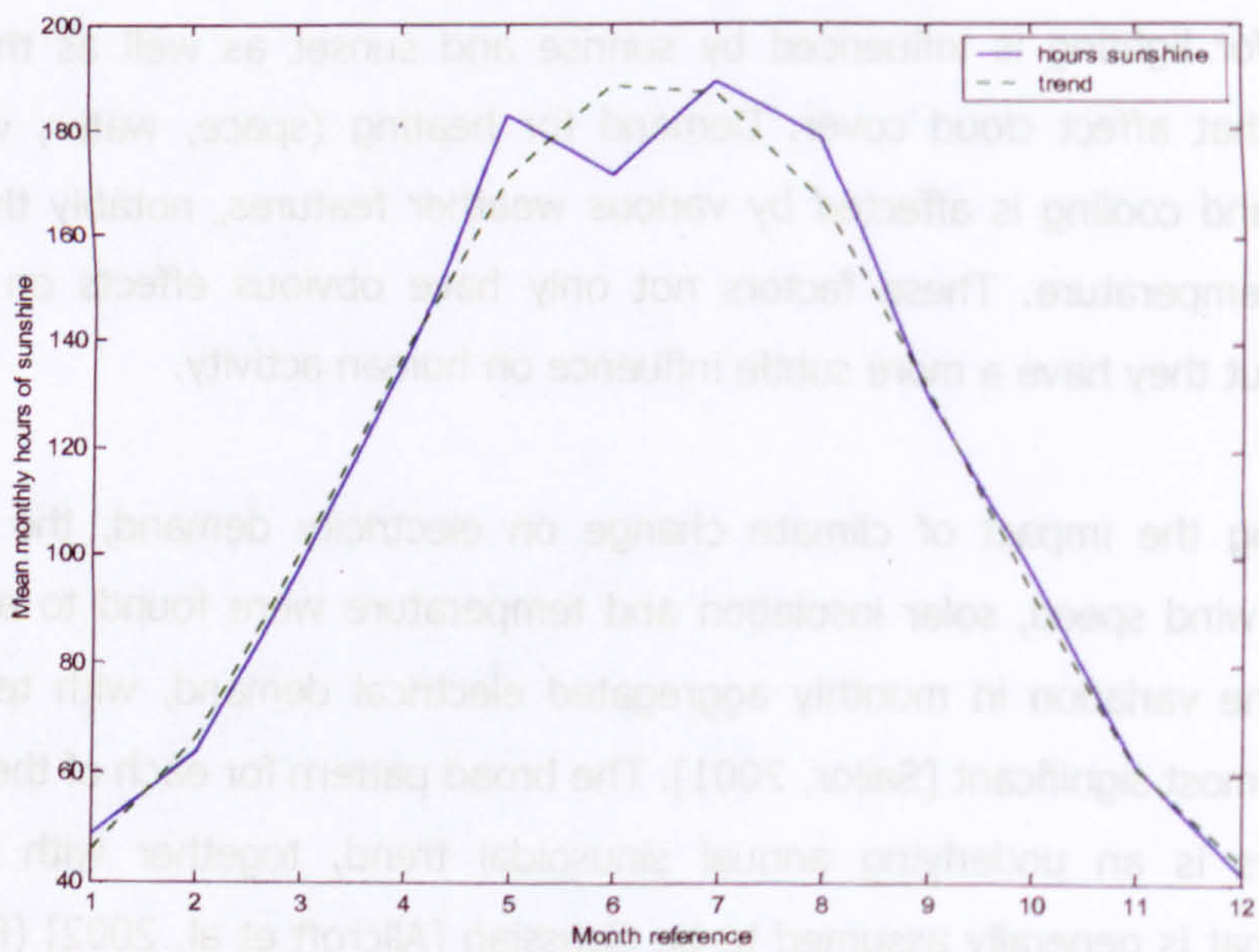


Figure 4-2: Typical annual pattern in the hours of sunshine (monthly mean values, 30 year averages 1971-2000 typical for Midlands [Met Office, 2004]

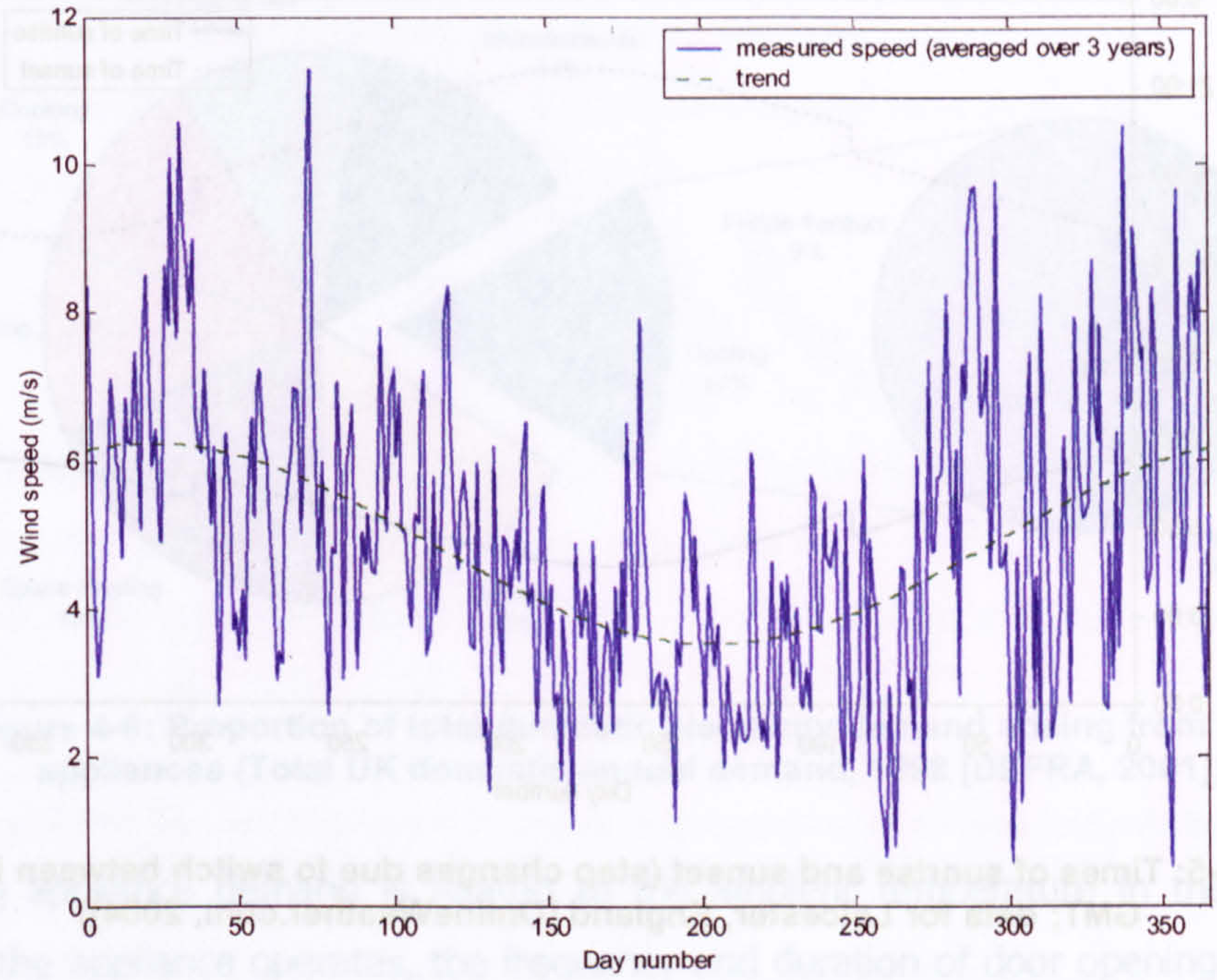


Figure 4-3: Typical annual pattern in the average daily wind speed (based on three year averages, where data available, 2002/4 for St. Leonards-on-Sea, East Sussex, England [Walton, 2004])

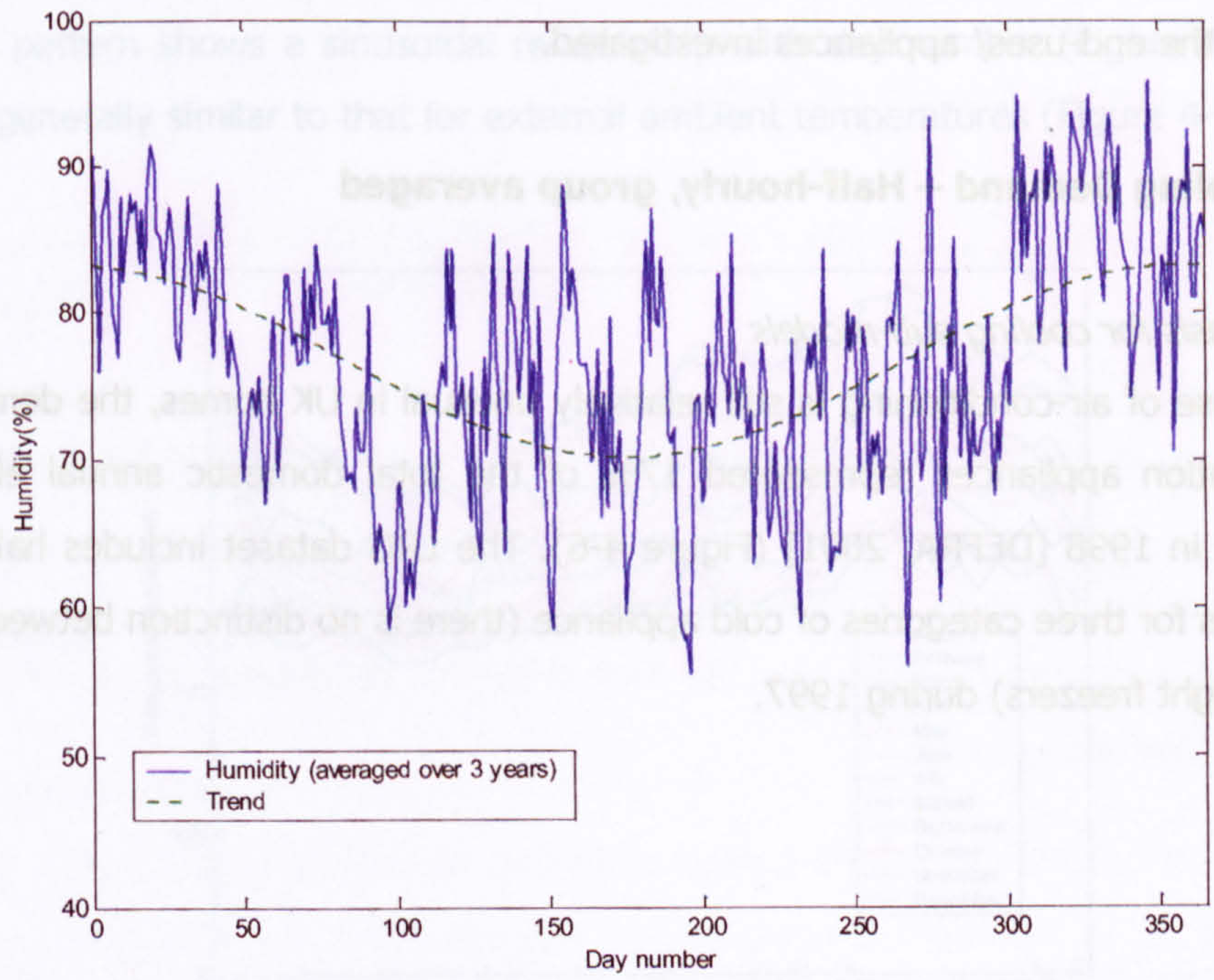


Figure 4-4: Typical annual pattern in the average daily humidity (based on 2003 data for St. Leonards-on-Sea,East Sussex, England [Walton,2004])

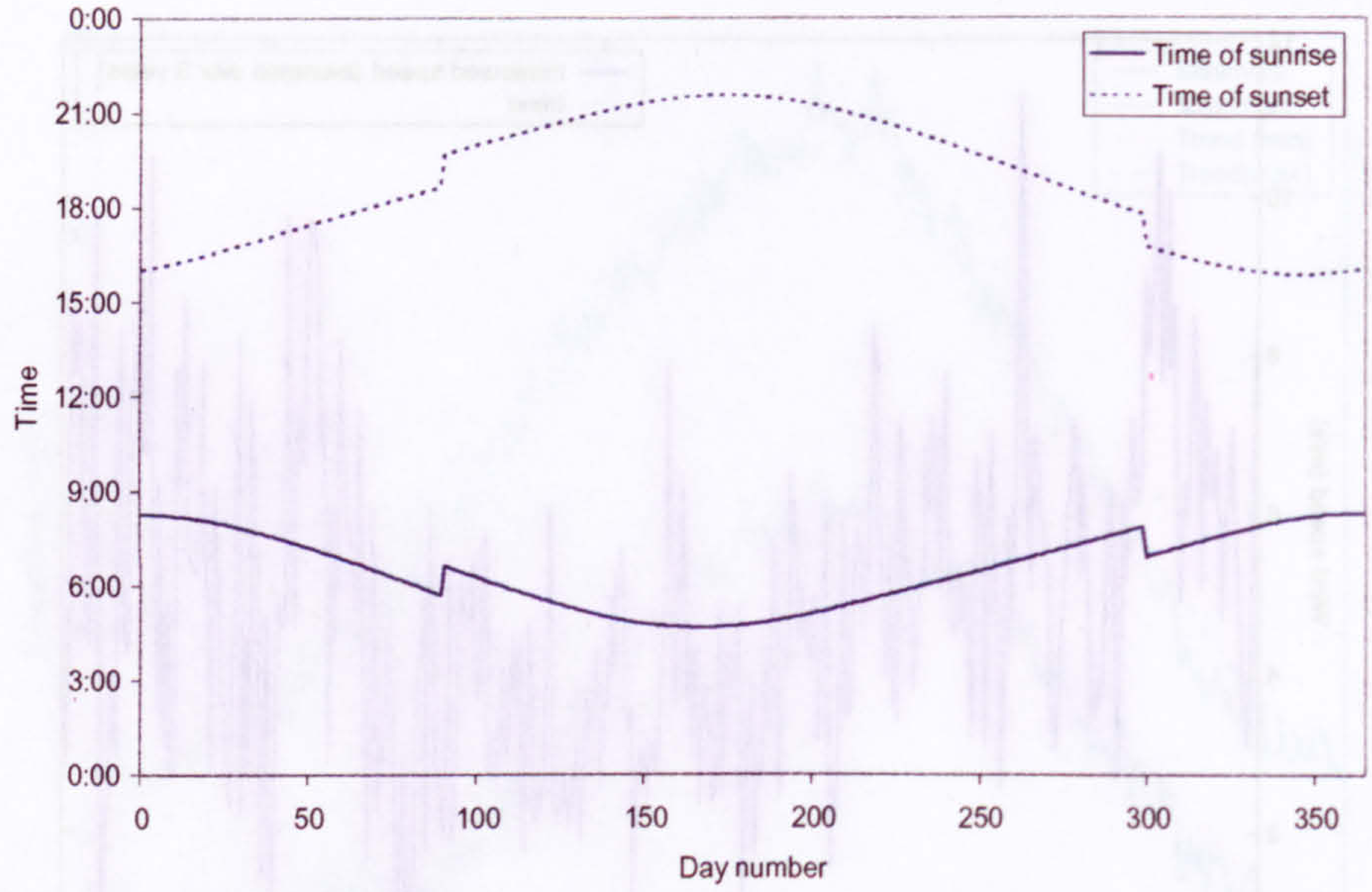


Figure 4-5: Times of sunrise and sunset (step changes due to switch between BST and GMT; data for Leicester, England [OnlineWeather.com, 2004])

Of course this basis is very similar to the annual relationships for the half-hourly electricity demand proposed in the last chapter (equation 3-2). In the following sections, these underlying sinusoidal trends and random components will be described in relation to the averaged half-hourly demand for a group of homes for each of the end-uses/ appliances investigated.

4.1 Cooling Demand – Half-hourly, group averaged

4.1.1 Basis for cooling sub-models

Whilst use of air-conditioning is still relatively unusual in UK homes, the demand for refrigeration appliances represented 17% of the total domestic annual electricity demand in 1998 [DEFRA, 2001] (Figure 4-6). The LRG dataset includes half-hourly demands for three categories of cold appliance (there is no distinction between chest and upright freezers) during 1997.

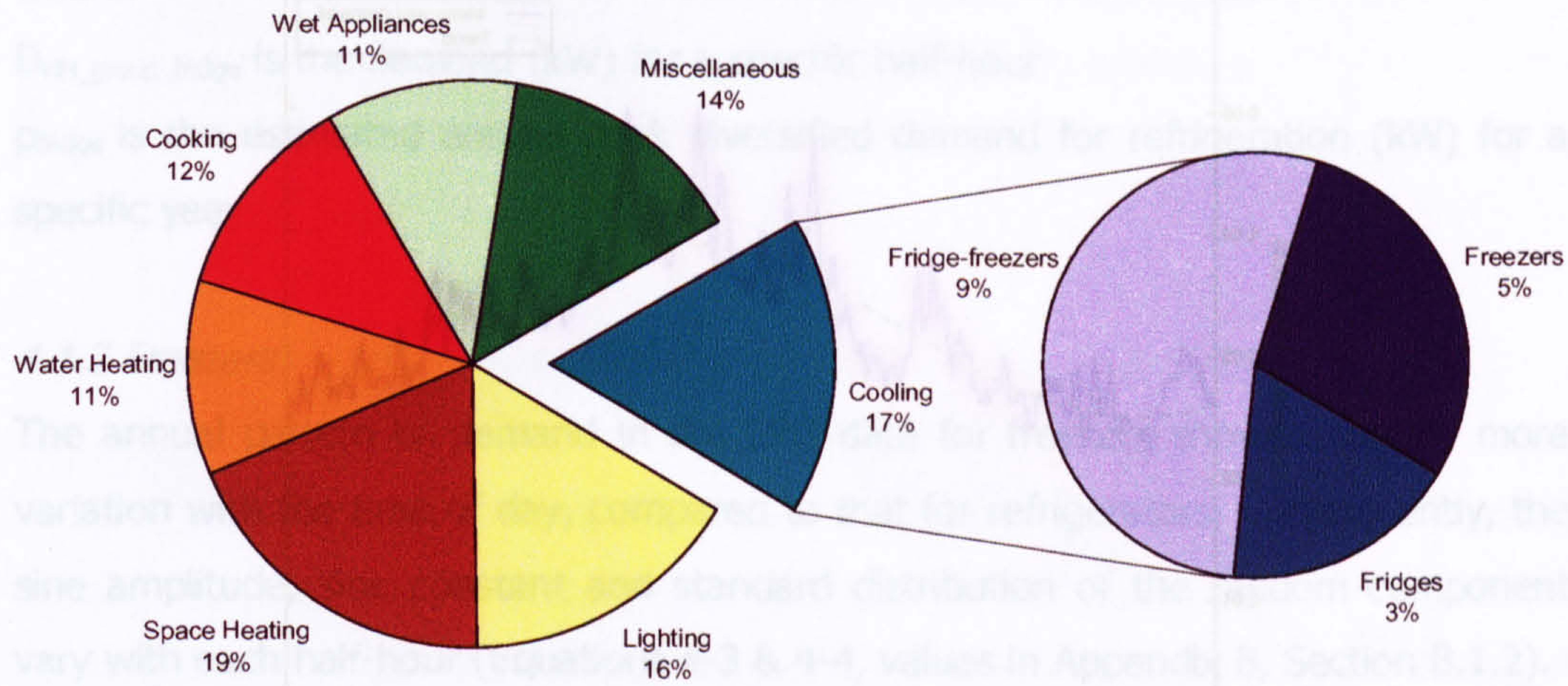


Figure 4-6: Proportion of total domestic electricity demand arising from cold appliances (Total UK domestic annual demand, 1998 [DEFRA, 2001])

Cooling appliance demand is related to the ambient temperature in the location where the appliance operates, the frequency and duration of door openings and the relative temperature of food placed inside. No significant weekly patterns emerge from analysing the LRG data, although strong daily and annual patterns occur in the cooling demand (Figures 4-7). The daily demand tends to peaks in the evening when activity in the home and the internal ambient temperatures are likely to be high. The annual pattern shows a sinusoidal relationship with day number (Figure 4-8), with phase generally similar to that for external ambient temperatures (Figure 4-1).

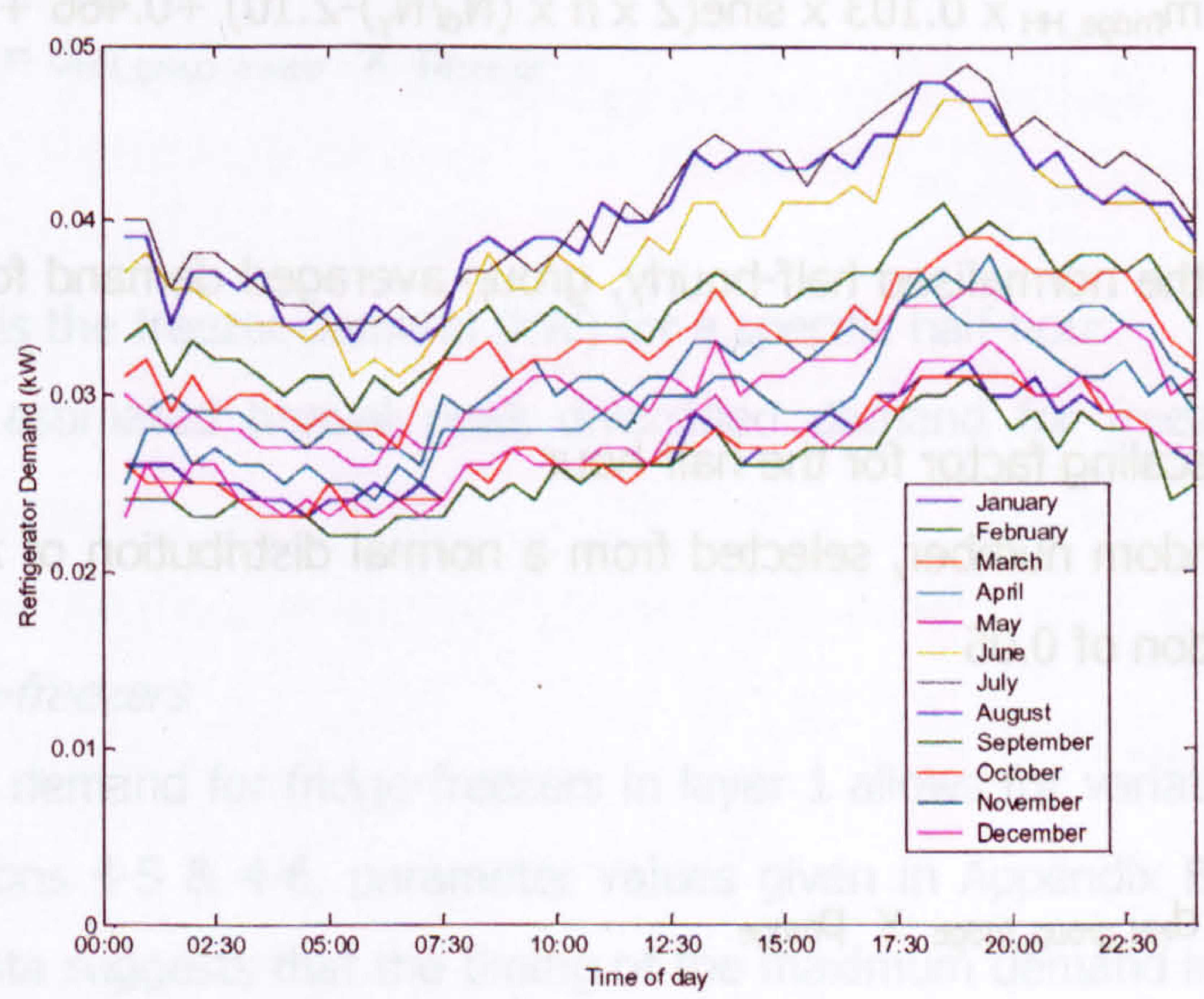


Figure 4-7: Daily pattern of demand for refrigeration (monthly averages, half-hourly demand, group averaged. Based on LRG data , 1996)

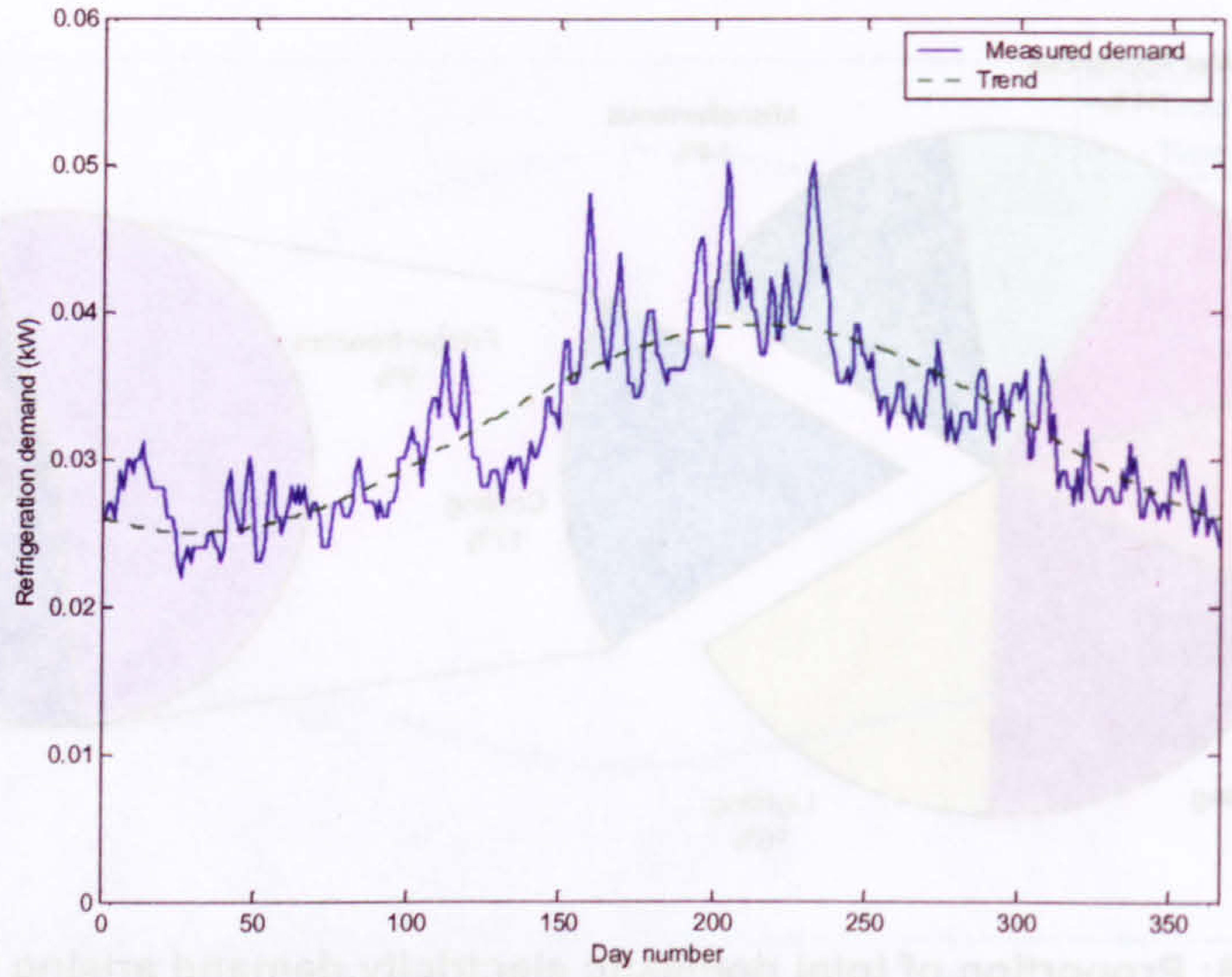


Figure 4-8: Annual pattern for refrigeration demand (averaged over all half-hours, half-hourly demand, group average. Based on LRG data, 1996)

4.1.2 Refrigerators

In the case of refrigerators, the annual trend for each half-hour of the day is very similar and the same annual pattern is used throughout the model (i.e. there is only one value for amplitude, phase and constant, regardless of the half-hour). The basic relationship is simply scaled for each half-hour (Equations 4-1 & 4-2, parameter values are given in Appendix B, Section B.1.1).

$$d_{HH\_group\_fridge} = m_{fridge\_HH} \times 0.103 \times \text{sine}(2 \times \pi \times (N_d/N_y)-2.10) + 0.466 + r_{HH\_fridge} \qquad \textbf{[4-1]}$$

where:

$d_{HH\_group\_fridge}$ is the normalised half-hourly, group averaged demand for a given half-hour

m_{fridge_HH} is the scaling factor for the half-hour

r_{fridge_HH} is a random number, selected from a normal distribution of zero mean and standard deviation of 0.05

and

$$D_{HH\_group\_fridge} = d_{HH\_group\_fridge} \times p_{fridge} \qquad \textbf{[4-2]}$$

where:

$D_{HH\_group\_fridge}$ is the demand (kW) for a specific half-hour

p_{fridge} is the estimated annual peak diversified demand for refrigeration (kW) for a specific year

4.1.3 Freezers

The annual pattern of demand in the LRG data for freezers showed slightly more variation with the time of day, compared to that for refrigerators. Consequently, the sine amplitude, sine constant and standard distribution of the random component vary with each half-hour (Equations 4-3 & 4-4, values in Appendix B, Section B.1.2).

$$d_{HH\_group\_freezer} = s_{freezer\_HH} \times \text{sine}(2 \times \pi \times (N_d/N_y)-2.05) + k_{freezer\_HH} + r_{freezer\_HH} \qquad \textbf{[4-3]}$$

where:

$d_{HH\_group\_freezer}$ is the normalised half-hourly, group averaged demand for a given half-hour

$s_{freezer\_HH}$ is the sine amplitude factor for the half-hour

$k_{freezer\_HH}$ is the sine constant

$r_{freezer\_HH}$ is a random number, selected from a normal distribution of zero mean and standard deviation of $\sigma_{freezer}$

and

$$D_{HH\_group\_freezer} = d_{HH\_group\_freezer} \times p_{freezer} \qquad \textbf{[4-4]}$$

where:

$D_{HH\_group\_freezer}$ is the freezer demand (kW) for a specific half-hour

$p_{freezer}$ is the estimated annual peak diversified demand for freezers (kW) for a specific year

4.1.4 Fridge-freezers

The modelled demand for fridge-freezers in layer 1 allows for variation in the phase angle (Equations 4-5 & 4-6, parameter values given in Appendix B, Section B.1.3) as the LRG data suggests that the timing of the maximum demand in the year varies slightly with the time of day (Figure 4-9).

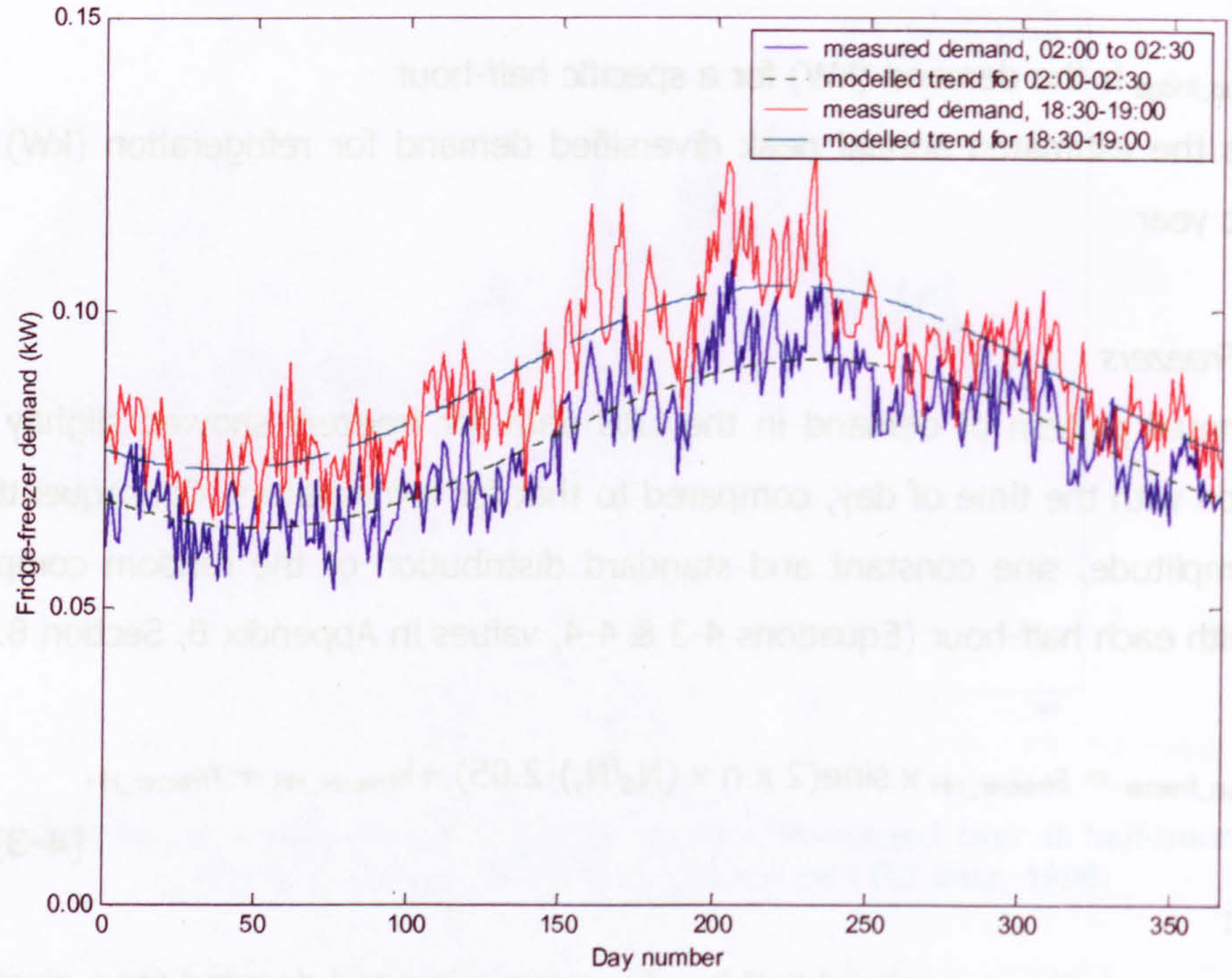


Figure 4-9: Annual pattern for fridge-freezer demand for early morning and late afternoon illustrating phase shift (half-hourly demand, group average. LRG data, 1996)

$$d_{HH\_group\_ff} = s_{ff\_HH} \times \text{sine}(2 \times \pi \times (N_d/N_y) - \varphi_{ff\_HH}) + k_{ff\_HH} + r_{ff\_HH} \quad \textbf{[4-5]}$$

where:

$d_{HH\_group\_ff}$ is the normalised half-hourly, group averaged demand for a given half-hour

s_{ff_HH} is the sine amplitude factor for the half-hour

φ_{ff_HH} is the sine phase angle

k_{ff_HH} is the sine constant

r_{ff_HH} is a random number, selected from a normal distribution of zero mean and standard deviation of σ_{ff}

and

$$D_{HH\_group\_ff} = d_{HH\_group\_ff} \times p_{ff} \quad \textbf{[4-6]}$$

where:

$D_{HH\_group\_ff}$ is the fridge-freezer demand (kW) for a specific half-hour

p_{ff} is the estimated annual peak diversified demand for fridge-freezers (kW) for a specific year

4.2 Space heating demand – half-hourly, group averaged

In 1998, use of electricity for space-heating accounted for 19% of the total domestic annual electricity demand (Figure 4-6). Increasingly, gas is being used in the UK for space and water heating, with less than 10% of homes using electricity – mainly in the form of fixed, storage radiators [DEFRA, 2001]. The LRG data for space heating relates solely to demand from electric storage heaters using off-peak electricity (electricity demand associated with other types of space heating – including pumps and controls for gas heating or portable electric heaters are included in the miscellaneous demand).

During the day, the demand is clearly high during the off-peak hours (Figure 4-10), typically 22:30 until 08:30 for the group, although only a 7 hour heating period within this range is likely for individual homes. Within the LRG group sample, there are likely to be variations in the local off-peak trigger timing and between different DNOs and tariffs. Consequently, the group-averaged demand builds from just before midnight to a peak in the early hours. Storage heaters generally use heating elements that operate at fixed demand levels, switching off when the core temperature of the storage medium (usually high-density bricks) reaches a manually selected pre-set level. The elements will switch in and out during the off-peak period to maintain the desired setting. During on-peak hours, there is a very low level, residual demand which may be due to the use of boost fans, manually switched to extract heat energy more quickly from the core. The LRG data shows that even during the summer months, demand can still exist at very low levels during the off-peak hours.

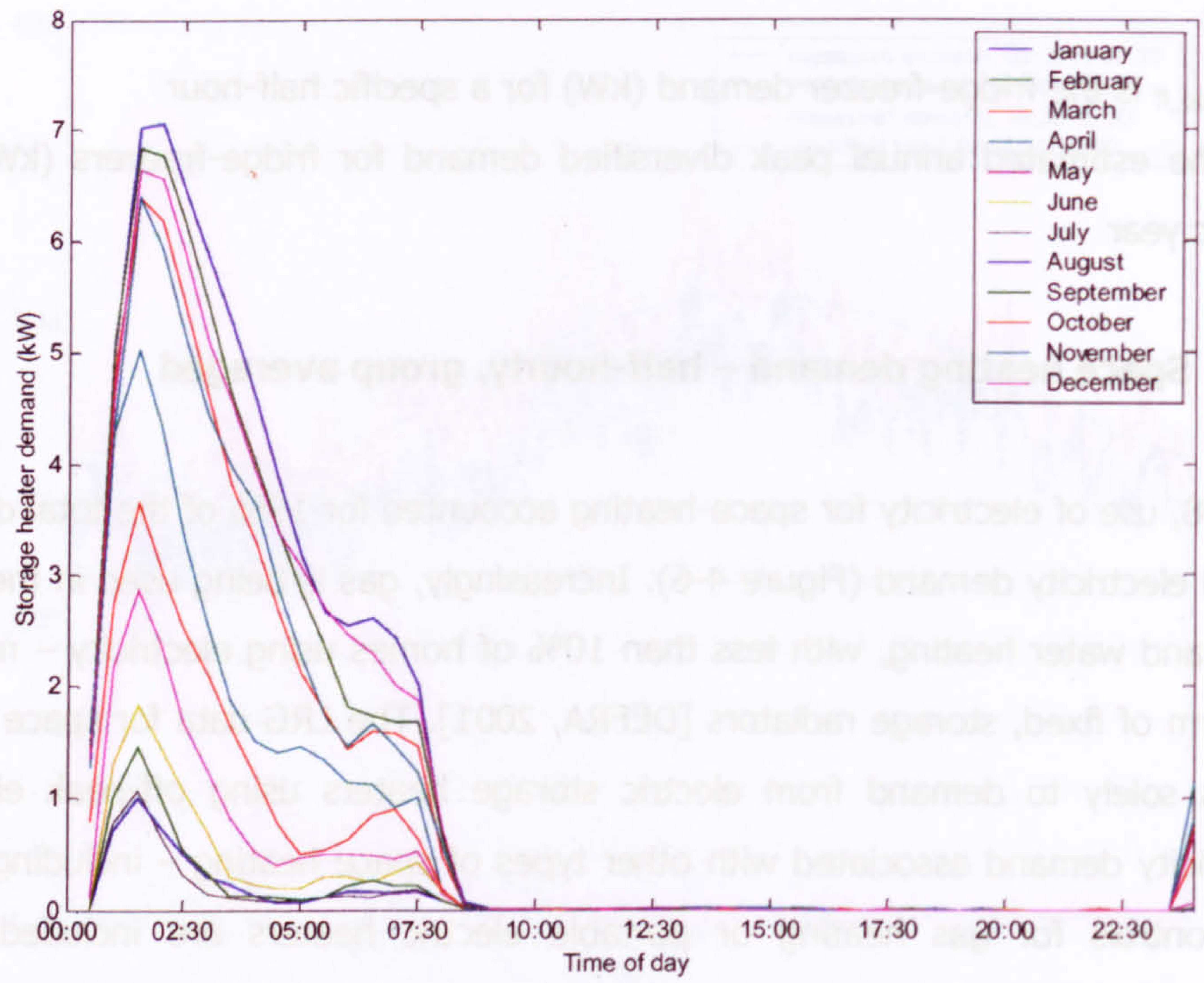


Figure 4-10: Daily pattern of demand for space heating (monthly averages, half-hourly demand, group averaged. Based on LRG data, 1999-2000)

The annual pattern in off-peak demand for storage heating is generally described by a minimum level, during the summer months, a maximum level, during early spring, winter and late autumn, with a sinusoidal component for the transition months. For consistency, the same pattern is adopted for on-peak hours (Figure 4-11). There was no significant weekly pattern in space heating demand observed in the LRG data and the same basis is applied for all day types (Equations 4-7 to 4-11, parameter values given in Appendix B, Section B.2).

$d_{heat\_sine} = s_{heat\_HH} \times \text{sine}(2 \times \pi \times (N_d/N_y) - \varphi_{heat\_HH}) + k_{heat\_HH}$ **[4-7]**

if $d_{heat\_max} \geq d_{heat\_sine} \geq d_{heat\_min}$, $d_{HH\_group\_heat} = d_{heat\_sine} + r_{heat\_HH}$ **[4-8]**

if $d_{heat\_sine} > d_{heat\_max}$, $d_{HH\_group\_heat} = d_{heat\_max} + r_{heat\_HH}$ **[4-9]**

if $d_{heat\_sine} < d_{heat\_min}$, $d_{HH\_group\_heat} = d_{heat\_min} + r_{heat\_HH}$ **[4-10]**

if $d_{heat\_HH\_group} < 0$, $d_{HH\_group\_heat} = 0$ **[4-11]**

where:

d_{heat_sine} is the underlying sinusoidal trend for storage space heating for a given half-hour

s_{heat_HH} is the sine amplitude factor for the half-hour

φ_{heat_HH} is the sine phase angle

k_{heat_HH} is the sine constant

d_{heat_max} is a maximum value for the trend

d_{heat_min} is a minimum value for the trend

r_{heat_HH} is a random number, selected from a normal distribution of zero mean and standard deviation of σ_{heat}

$d_{HH\_group\_heat}$ is the normalised half-hourly, group averaged demand for a given half-hour for storage space heating

No reliable trends have been found for domestic demand for storage space heating with electricity. The annual peak demand for the 1999/2000 LRG data was 7.649 kW and the model uses this value for all years to derive the group averaged heating demand (equation 4-12).

$$D_{HH\_group\_heat} = d_{HH\_group\_heat} \times 7.649 \qquad \textbf{[4-12]}$$

where:

$D_{HH\_group\_heat}$ is the space heating demand (kW) for a specific half-hour

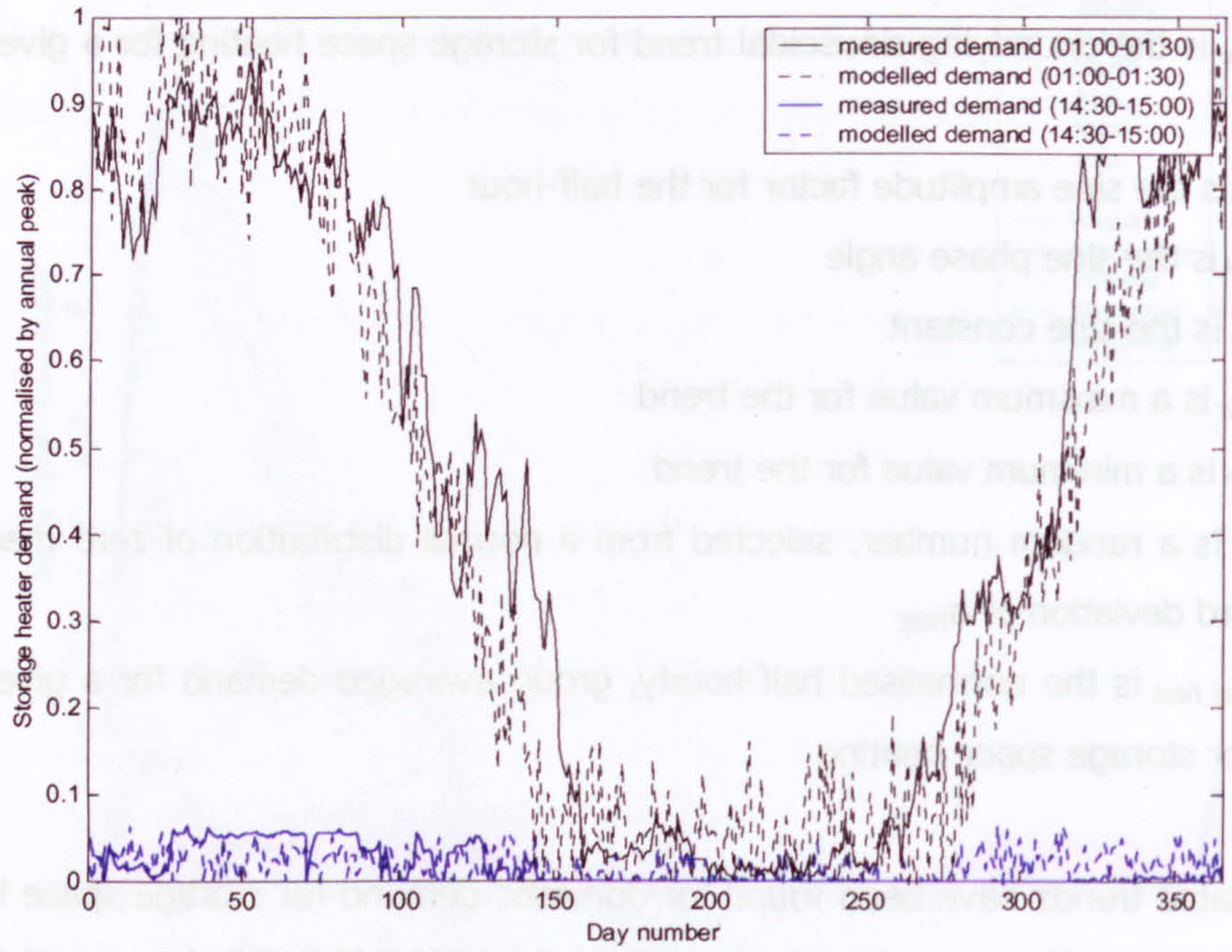


Figure 4-11: Annual pattern of demand for space heating for on-peak and off-peak demand (normalised, half-hourly demand, group averaged. Based on LRG data, 1999-2000)

4.3 Water heating demand – half-hourly, group averaged

Electricity for domestic water heating represented 11% [DEFRA, 2001] of the total annual domestic electricity demand in the UK for 1998 (Figure 4.6). This demand is generally declining as more homes use gas for both space and water heating. The most common systems for electrical water heating involve immersion heating coils within a hot water tank. The LRG data refer only to this type of water heater (other systems, such as instantaneous heaters, are considered to contribute to the miscellaneous demand) and provide demand values for both unrestricted and off-peak consumers. Although the majority of UK homes have immersion coils fitted in the water tank (currently estimated at 63%), few are actually used, with an estimated 26% in use all year round and 15% during the summer only [DEFRA, 2001]. It is unknown whether or not the LRG data includes consumers with different patterns of use and as the sample sizes are small (16 unrestricted tariff consumers and 22 Economy-7 consumers) the underlying trends in demand are less obvious than those for other end-uses and appliances.

The daily pattern of demand for water heating is clearly influenced by the use of cheap rate off-peak electricity for Economy-7 consumers during the early hours although water tends to be reheated in the evening using electricity at a higher cost (Figure 4-12). The daily profile for consumers on unrestricted tariffs was relatively flat with very little variation in demand across the day. No clear weekly patterns were found in the data and the annual pattern showed a weak sinusoidal trend (Figure 4-13). Demand is based on equations 4-13 to 4-15 (parameter values in Appendix B, section B.3).

$$d_{HH\_group\_water} = s_{water\_HH} \times \text{sine}(2 \times \pi \times (N_d/N_y) - \varphi_{water\_HH}) + k_{water\_HH} + r_{water} \quad [4\text{-}13]$$

$$\text{if } d_{HH\_group\_water} < 0,\ d_{HH\_group\_water} = 0 \quad [4\text{-}14]$$

where:

$d_{HH\_group\_water}$ is the normalised half-hourly, group averaged demand for water heating in a given half-hour

s_{water_HH} is the sine amplitude factor for the half-hour

φ_{water_HH} is the sine phase angle

k_{water_HH} is the sine constant

r_{water_HH} is a random number, selected from a normal distribution of zero mean and standard deviation of σ_{water}

and

$$D_{HH\_group\_water} = d_{HH\_group\_water} \times p_{water} \quad [4\text{-}15]$$

where:

$D_{HH\_group\_water}$ is the water heating demand (kW) for a specific half-hour

p_{water} is the estimated annual peak diversified demand for water heating (kW) for a specific year

Parameter values (both unrestricted and Economy-7 tariffs) for calculating water heating demand are given in Tables B-8 to B-10.

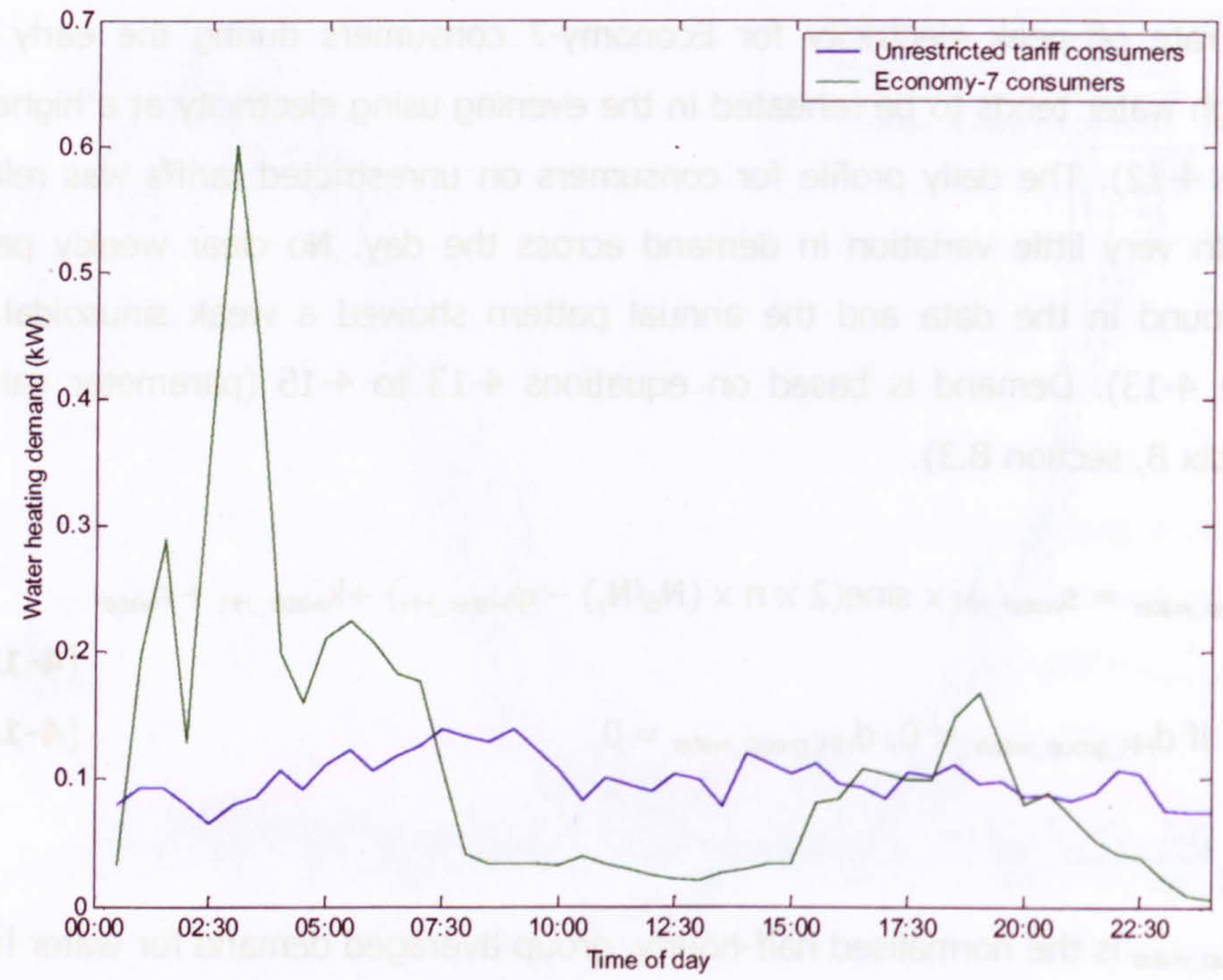


Figure 4-12: Daily pattern of demand for water heating (annual average, half-hourly demand, group averaged. Based on LRG data, 1999-2000)

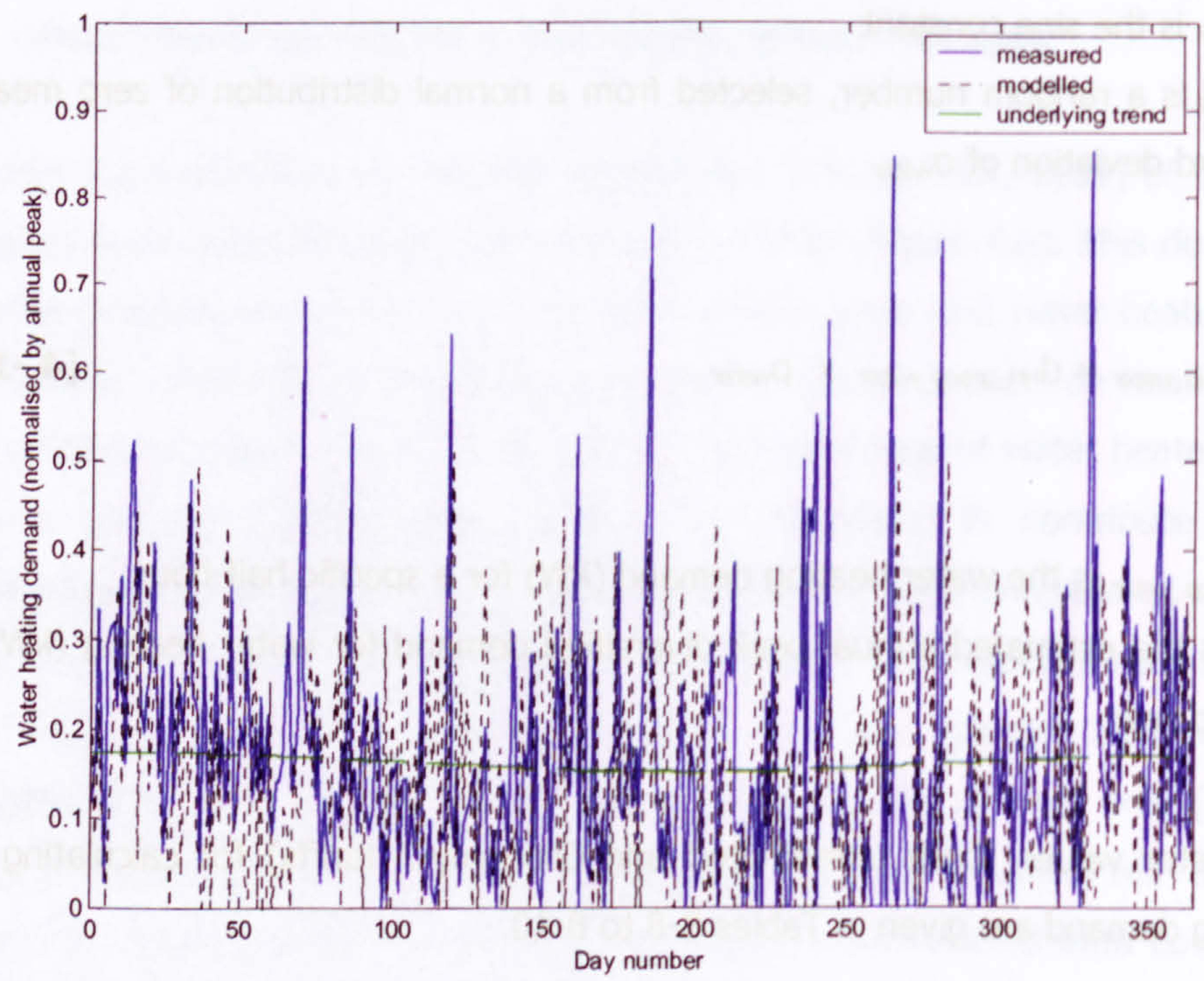


Figure 4-13: Annual pattern of demand for water heating between 07:30 and 08:00 (unrestricted tariff, normalised, half-hourly demand, group averaged. Based on LRG data, 1999-2000)

4.4 Cooking demand – half-hourly, group averaged

In 1998, 12% of the total annual domestic electricity consumption arose from cooking appliances. This represented a demand of around 13,000 GWh which is expected to rise by more than 8% by 2020. However, increasingly microwaves are used for warming pre-cooked meals and gas is the preferred fuel for hobs whilst electricity continues to be chosen for cooking in ovens [DEFRA,2001].

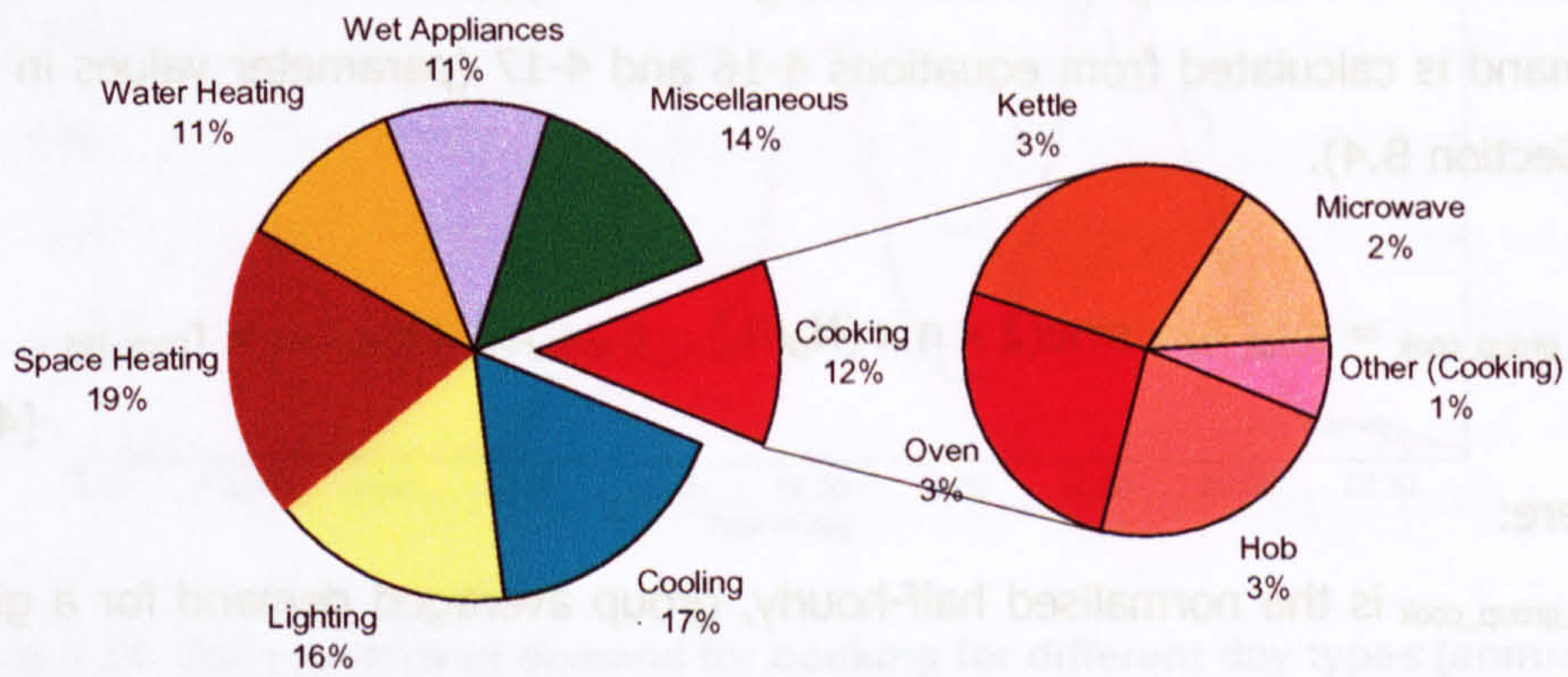


Figure 4-14: Proportion of total domestic electricity demand arising from cooking appliances (Total UK domestic annual demand, 1998 [DEFRA, 2001])

The LRG dataset provides half-hourly demands for cooking as a single category, during 1996. There is no distinction between consumers on different tariffs since cooking is rarely scheduled to take advantage of cheaper off-peak rates. Since the various cooking appliances have very different duty cycles and patterns of ownership and since the spikes in 1-minute demand are often related to the use of kettles and hobs, it was important for the domestic model to consider hobs, ovens, kettles and microwaves separately. Obviously the use of cooking appliances is related to mealtimes and the demand inversely follows the trend in external ambient temperature. For the domestic model, the assumption is made that the same underlying daily, weekly and annual patterns of demand can be used for these four cooking appliances.

The daily profiles of demand show clear peaks around mid-day and in the early evening. Cooking demand is minimal during the night. Traditionally in the UK, Sunday lunch is the most significant meal of the week and the LRG data confirm this, with much higher levels of demand around mid-day on Sunday compared to other days of the week (Figure 4-15). There are smaller differences between demand on Saturdays and other weekdays, with a slightly higher demand at lunchtimes and lower demand in the evening on Saturdays. The domestic demand model captures the distinct differences between weekdays, Saturdays and Sundays.

The annual pattern in cooking demand has an underlying sinusoidal trend against day number that is the approximately the inverse of that for ambient external temperatures (Figure 4-16, note the greater day-to-day fluctuations in demand during late December, probably due to Christmas preparations and meals).The values for the cooking variables are given in Appendix B, Section B.4. Cooking demand is calculated from equations 4-16 and 4-17 (parameter values in Appendix B, Section B.4).

$$d_{HH\_group\_cook} = s_{cook\_HH} \times \text{sine}(2 \times \pi \times (N_d/N_y) - \varphi_{cook\_HH}) + k_{cook\_HH} + r_{cook\_HH} \qquad [4\text{-}16]$$

where:

$d_{HH\_group\_cook}$ is the normalised half-hourly, group averaged demand for a given half-hour

s_{cook_HH} is the sine amplitude factor for the half-hour

φ_{cook_HH} is the sine phase angle

k_{cook_HH} is the sine constant

r_{cook_HH} is a random number, selected from a normal distribution of zero mean and standard deviation of σ_{cook}

and

$$D_{HH\_group\_cook} = d_{HH\_group\_cook} \times p_{cook} \qquad [4\text{-}17]$$

where:

$D_{HH\_group\_cook}$ is the cooking demand (kW) for a specific half-hour on one of three day types

p_{cook} is the estimated annual peak diversified demand for cooking appliances (kW) in a specific year

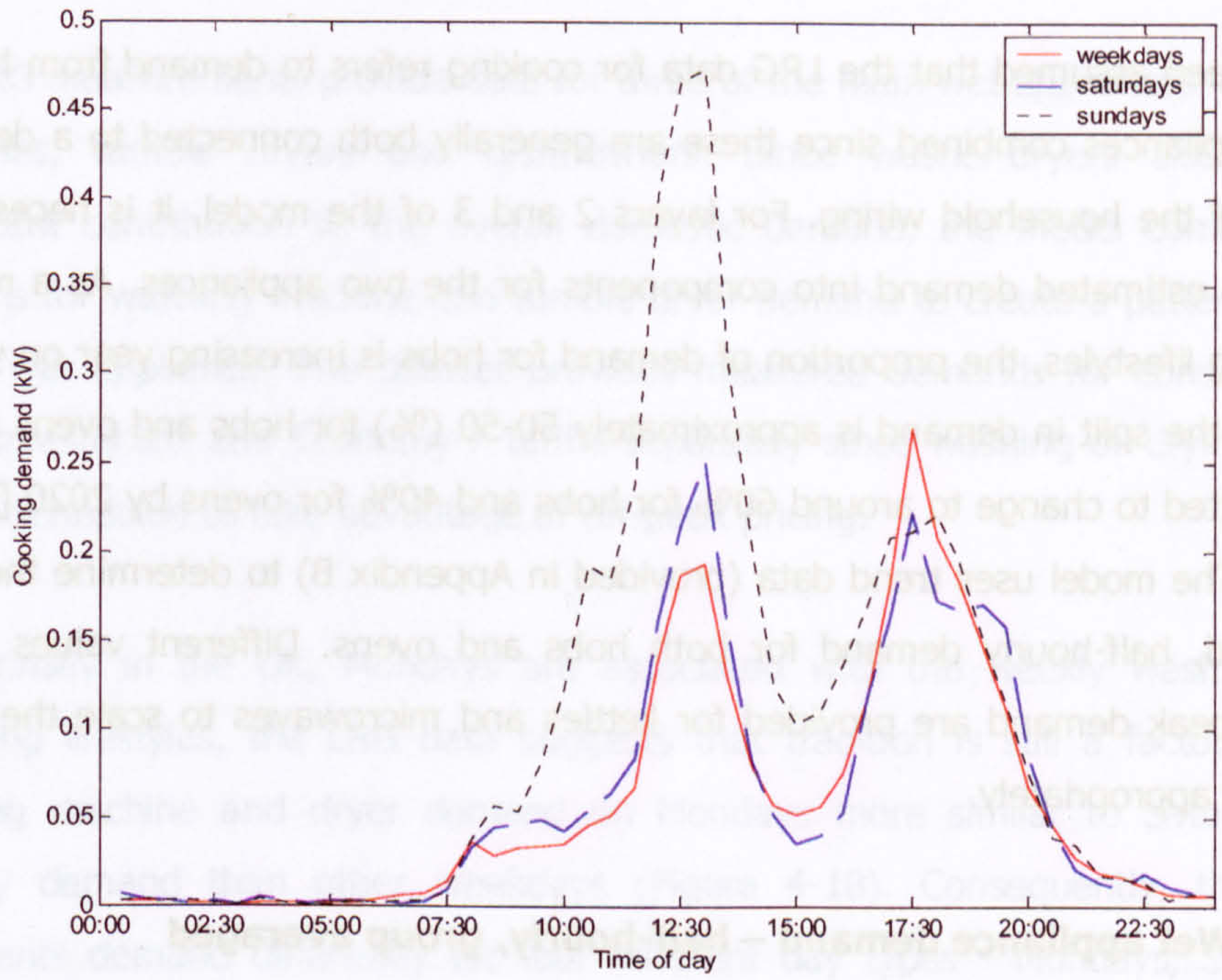


Figure 4-15: Daily pattern of demand for cooking for different day types (annual averages, half-hourly demand, group averaged. Based on LRG data, 1996)

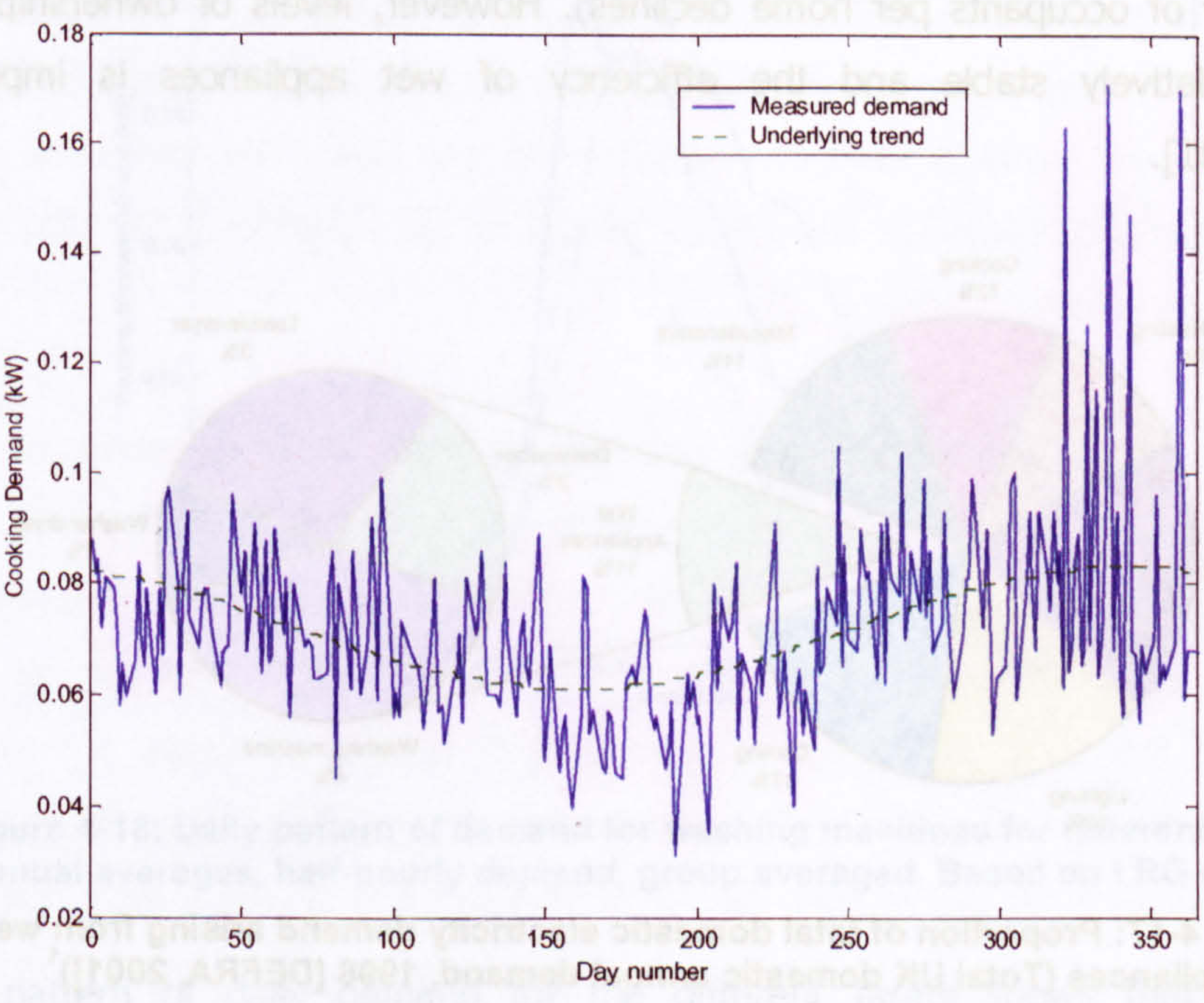


Figure 4-16: Annual pattern for cooking demand on weekdays (averaged over all half-hours, half-hourly demand, group average. Based on LRG data, 1996)

It has been assumed that the LRG data for cooking refers to demand from hob and oven appliances combined since these are generally both connected to a dedicated circuit of the household wiring. For layers 2 and 3 of the model, it is necessary to split the estimated demand into components for the two appliances. As a result of changing lifestyles, the proportion of demand for hobs is increasing year on year. At present the split in demand is approximately 50-50 (%) for hobs and ovens but this is predicted to change to around 60% for hobs and 40% for ovens by 2020 [DEFRA, 2001]. The model uses trend data (provided in Appendix B) to determine the group averaged, half-hourly demand for both hobs and ovens. Different values for the annual peak demand are provided for kettles and microwaves to scale the annual patterns appropriately.

4.5 Wet appliance demand – half-hourly, group averaged

Wet appliances include washing machines, tumble-dryers, combined washer-dryers and dishwashers. Together, these appliances accounted for 11% of the total annual UK domestic electricity consumption in 1998. The aggregated annual demand shows an upward trend, largely because the housing stock in the UK continues to increase (as number of occupants per home declines). However, levels of ownership have become relatively stable and the efficiency of wet appliances is improving [DEFRA,2001].

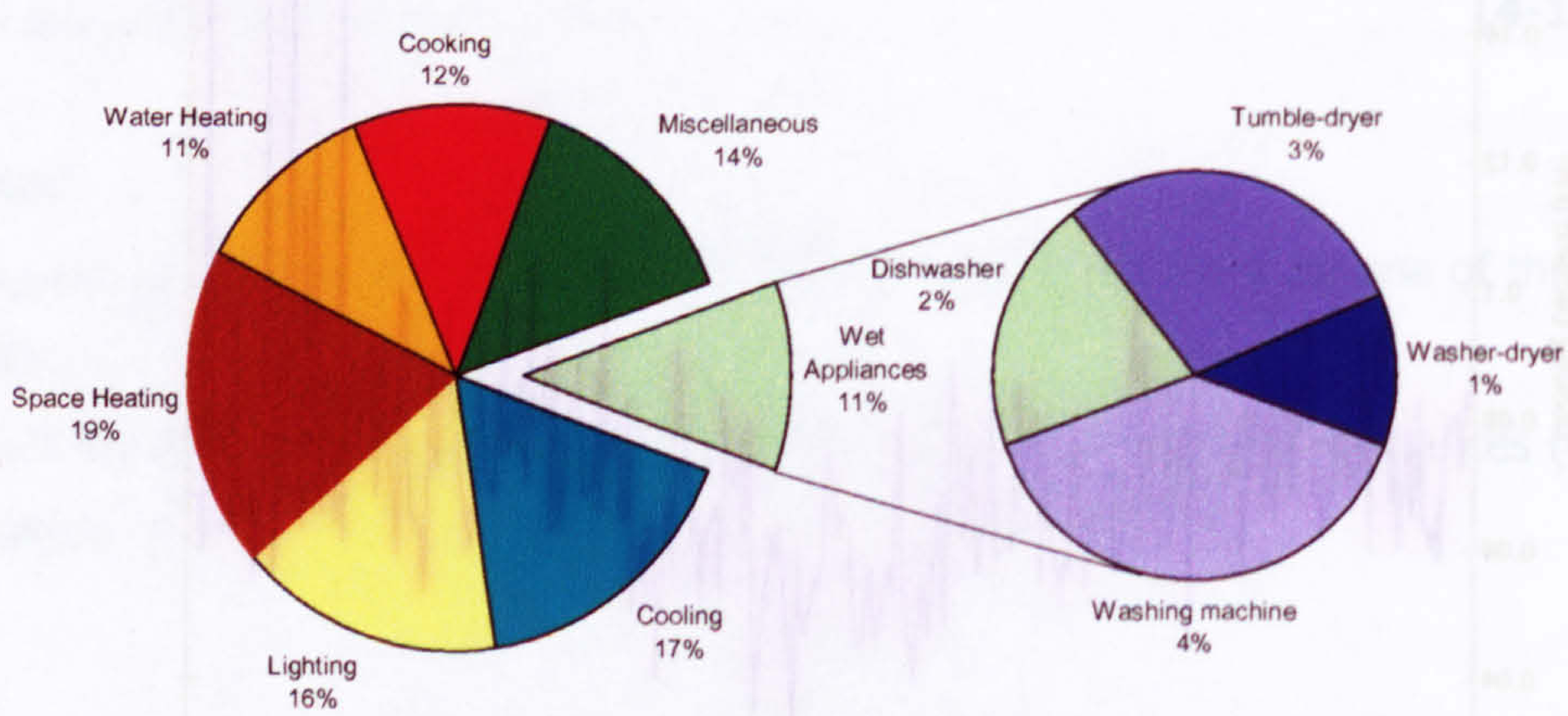


Figure 4-17: Proportion of total domestic electricity demand arising from wet appliances (Total UK domestic annual demand, 1998 [DEFRA, 2001])[1]

[1] Apparent discrepancy in the contributions of the individual wet appliances and that for wet appliances as a whole is due to rounding errors

The LRG measurements provide data for three of the main wet appliances – washing machines, tumble dryers and dishwashers. Since washer-dryers also have a significant contribution to the overall domestic demand, the model combines the patterns for washing machine and tumble-dryer demand to create a pattern for the fourth wet appliance. The dataset provides measured demands for consumers on both unrestricted and Economy-7 tariffs separately since washing or drying events can be scheduled to take advantage of off-peak pricing.

Traditionally in the UK, Mondays are associated with the weekly wash. Despite changing lifestyles, the LRG data suggests that tradition is still a factor, making washing machine and dryer demand on Mondays more similar to Saturday and Sunday demand than other weekdays (Figure 4-18). Consequently, the model represents demand differently for four different day types - Mondays, Saturdays, Sundays and other weekdays. The weekly profile for dishwasher demand was far less clear and the same pattern is used regardless of day type.

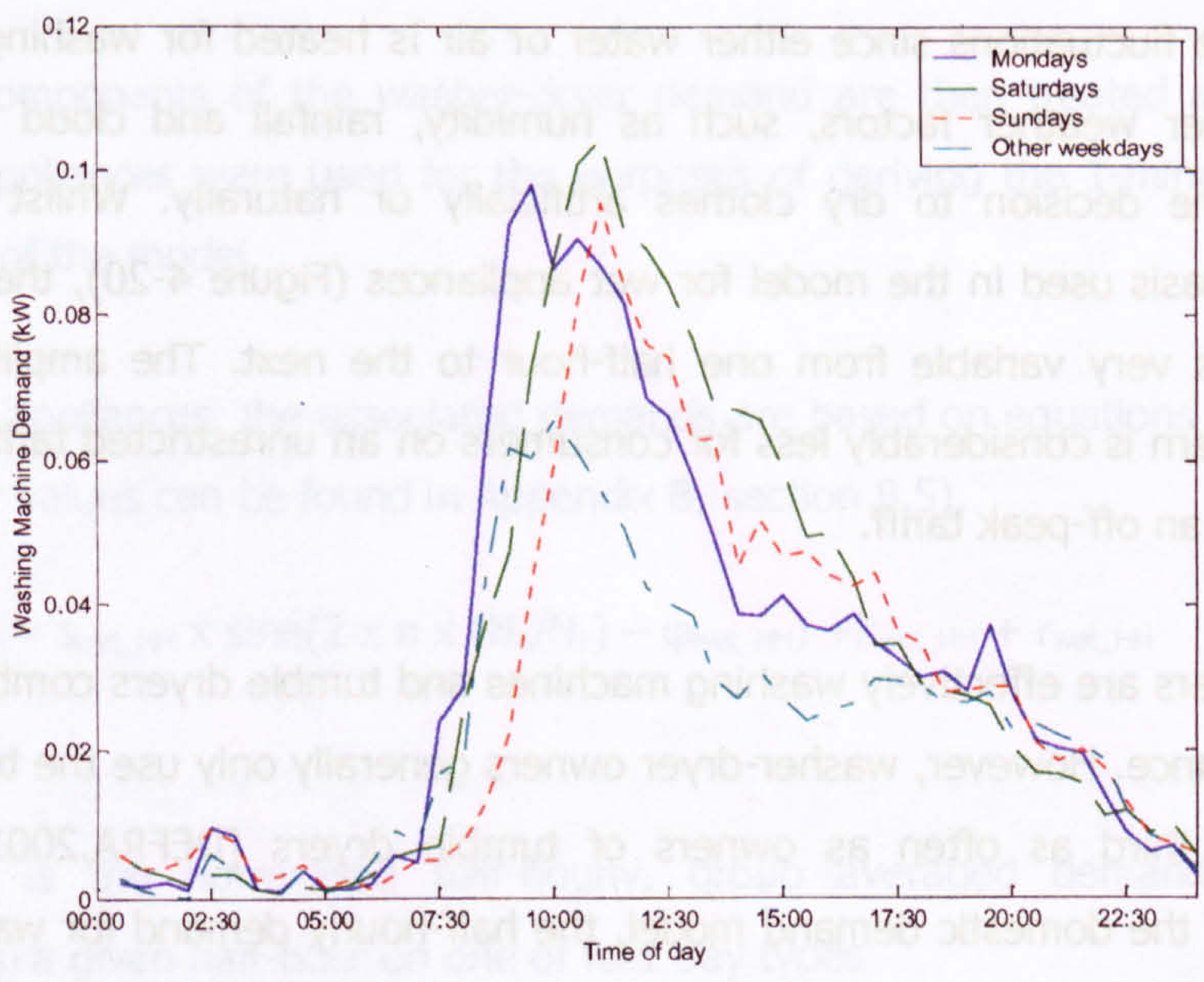


Figure 4-18: Daily pattern of demand for washing machines for different day types (annual averages, half-hourly demand, group averaged. Based on LRG data, 1996)

The pattern of daily demand for the different tariffs shows that for all wet appliances, consumers take some advantage of the off-peak pricing by scheduling demand more during the early morning and less in the late evening (Figure 4-19).

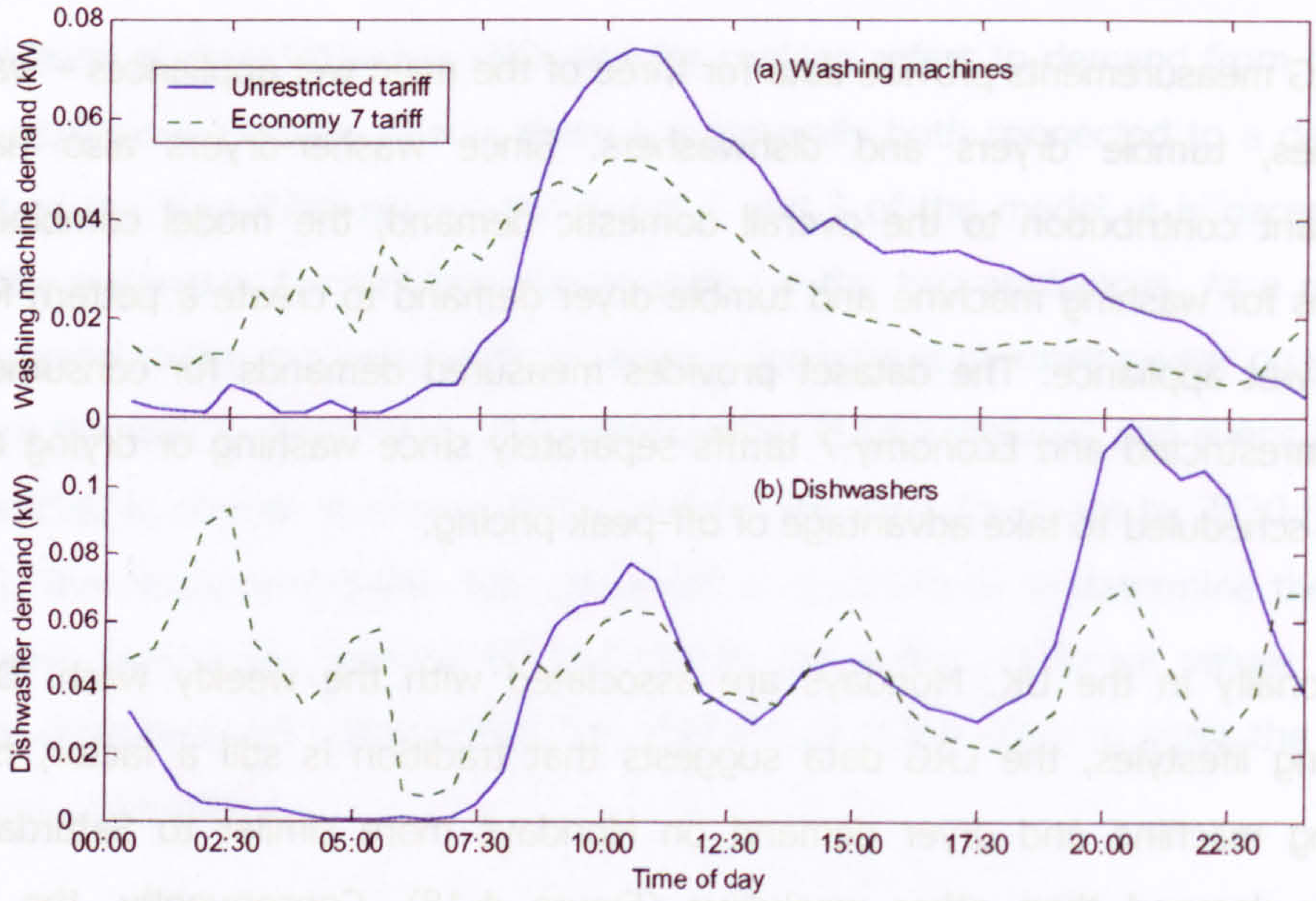


Figure 4-19: Variation in daily pattern of demand for washing machines and dishwashers depending on tariff used (annual averages, over all days, half-hourly demand, group averaged. Based on LRG data, 1996)

Electricity demand from wet appliances is weakly related to external ambient temperature fluctuations since either water or air is heated for washing or drying. Various other weather factors, such as humidity, rainfall and cloud cover, may influence the decision to dry clothes artificially or naturally. Whilst there is a sinusoidal basis used in the model for wet appliances (Figure 4-20), the phasing of the trend is very variable from one half-hour to the next. The amplitude of the annual pattern is considerably less for consumers on an unrestricted tariff compared to those on an off-peak tariff.

Washer dryers are effectively washing machines and tumble dryers combined in one single appliance. However, washer-dryer owners generally only use the tumble dryer cycles one third as often as owners of tumble dryers [DEFRA,2001]. For the purposes of the domestic demand model, the half-hourly demand for washer-dryers is taken as the sum of the half-hourly demand trends calculated for washing machines and one third of the demand for tumble dryers. This assumption neglects possible differences in the relative timing of washing and drying events compared with that for the separate appliances although this unlikely to have a major effect on the simulations of the total loading over a network area.

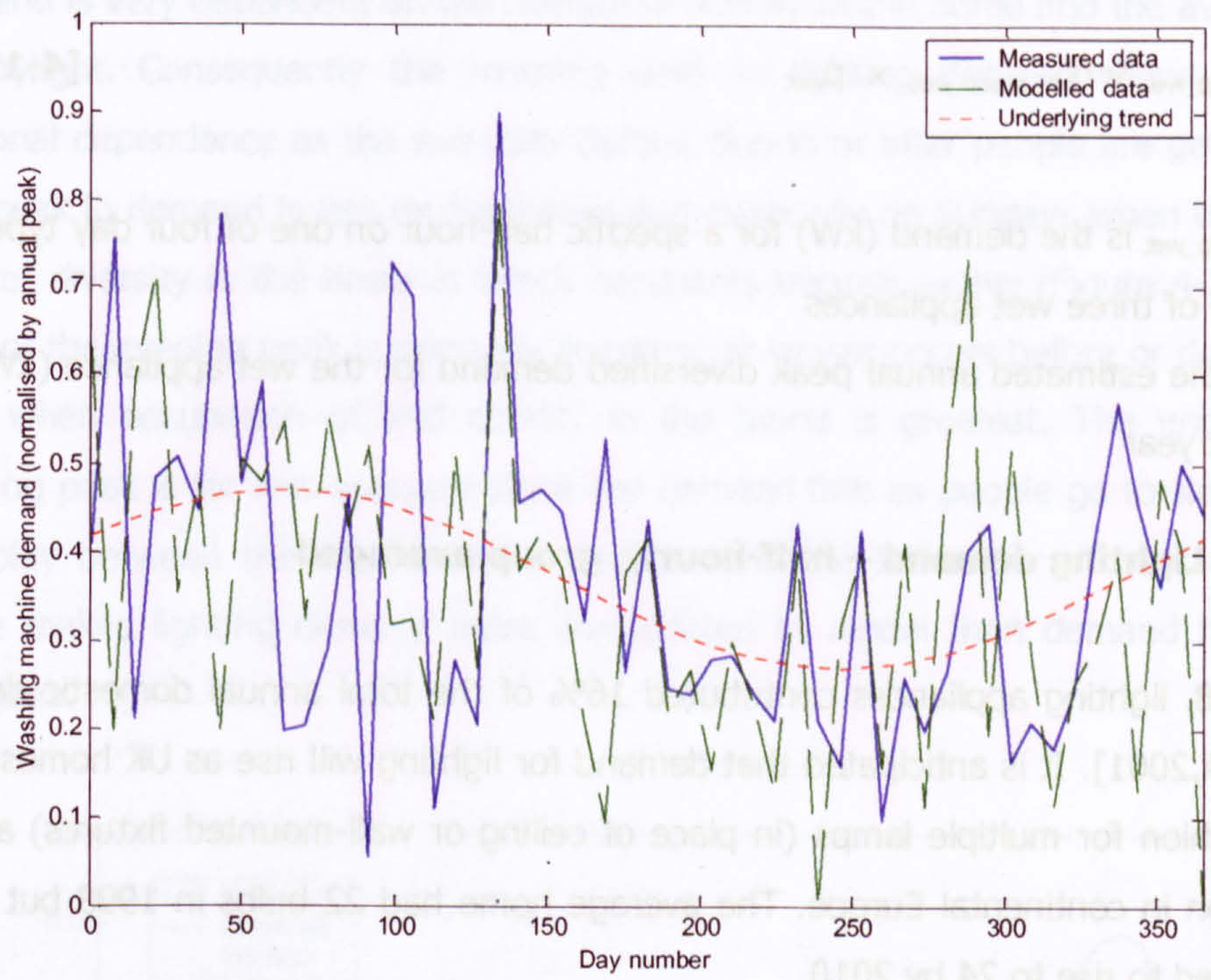


Figure 4-20: Annual pattern for washing demand on Mondays between 10:30-11:00 (unrestricted tariff, half-hourly demand, group average. Based on LRG data, 1996)

The two components of the washer-dryer demand are then treated as if the two separate appliances were used for the purposes of deriving the 1-minute demands for layer 3 of the model.

For all wet appliances, the associated demands are based on equations 4-18 to 4-19 (parameter values can be found in Appendix B, section B.5).

$$d_{HH\_group\_wet} = s_{wet\_HH} \times \text{sine}(2 \times \pi \times (N_d/N_y) - \varphi_{wet\_HH}) + k_{wet\_HH} + r_{wet\_HH} \quad [4\text{-}18]$$

where:

$d_{HH\_group\_wet}$ is the normalised half-hourly, group averaged demand for a wet appliance in a given half-hour on one of four day types

s_{wet_HH} is the sine amplitude factor for the half-hour

φ_{wet_HH} is the sine phase angle

k_{wet_HH} is the sine constant

r_{wet_HH} is a random number, selected from a normal distribution of zero mean and standard deviation of σ_{wet}

and

$D_{HH\_group\_wet} = d_{HH\_group\_wet} \times p_{wet}$ **[4-19]**

where:

$D_{HH\_group\_wet}$ is the demand (kW) for a specific half-hour on one of four day types and for one of three wet appliances

p_{wet} is the estimated annual peak diversified demand for the wet appliance (kW) in a specific year

4.6 Lighting demand – half-hourly, group averaged

In 1998, lighting appliances contributed 16% of the total annual domestic demand [DEFRA,2001]. It is anticipated that demand for lighting will rise as UK homes adopt the fashion for multiple lamps (in place of ceiling or wall-mounted fixtures) already common in continental Europe. The average home had 22 bulbs in 1998 but this is predicted to rise to 24 by 2010.

The daily pattern for lighting demand is characterised by two peaks, one around breakfast-time and another broader peak in the evening (Figure 4-21).

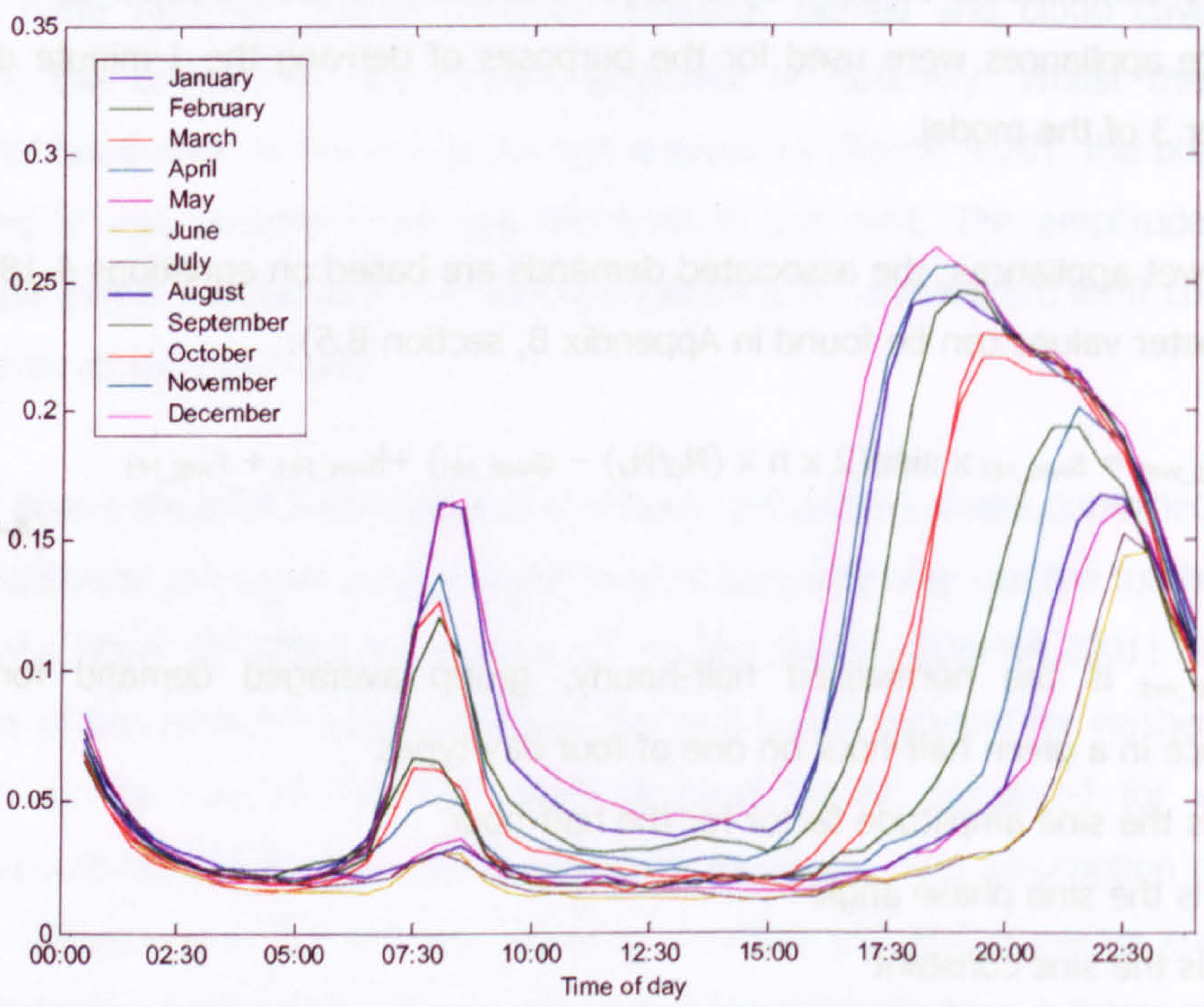


Figure 4-21: Daily pattern of demand for lighting (for weekdays, monthly averages, half-hourly demand, group averaged. Based on LRG data for 1996/7)

Demand is very dependent on the overlap of activity in the home and the availability of daylight. Consequently the morning peak in lighting demand shows a large seasonal dependence as the sun rises before, during or after people are getting up. The peak in demand is less on Saturdays and especially on Sundays when there is a greater diversity in the times at which occupants become active (Figure 4-22). The start of the evening peak is also very seasonal as sunset occurs before or during the time when occupation of and activity in the home is greatest. The end of the evening peak is far less seasonal since the demand falls as people go to sleep. This interplay between the availability of daylight and the behaviour of people in the home makes lighting demand more complicated to model than demand for other end-uses.

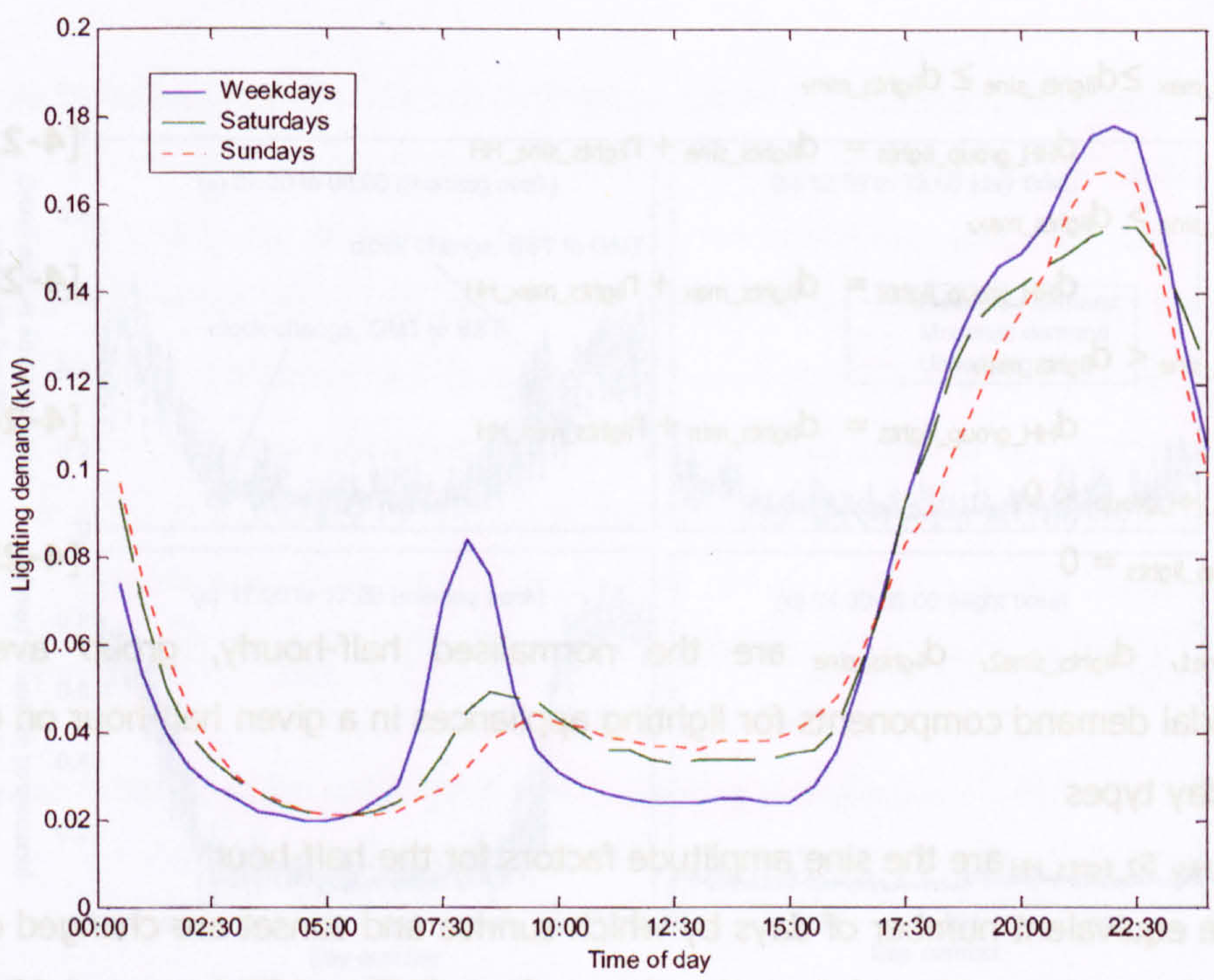


Figure 4-22: Daily pattern of demand for lighting showing dependence on day type (annual averages, half-hourly demand, group averaged. Based on LRG data for 1996/7)

The annual trends in demand vary greatly depending on the time of day and it is necessary to use four components to model it (Figure 4-23). A minimum lighting demand level applies, when sunrise occurs at least 90 minutes before or sunset occurs at least 90 minutes after the half-hour in question (i.e. potential for maximum levels of daylight). A maximum level is used, when sunrise is at least 90 minutes after or sunset 90 minutes before the half-hour (i.e. no daylight available). The transition between these demand levels is modelled by a combination of two sinusoidal components – with either a positive or negative phase shift of 34 days between the dates of clock change from GMT to BST and vice versa (02:00 on the nearest Sunday to the 31st March and the 31st October). This phase shift allows the step increase or decrease in demand that occurs when the clocks are changed.

Demand is calculated from equations 4-20 to 4-26 (parameter values appear in Appendix B, section B.6).

$$d_{lights\_sine1} = s_{1\_lights\_HH} \times \text{sine}(2 \times \pi \times ((N_d + n)/N_y) - \varphi_{1\_lights\_HH}) \quad \textbf{[4-20]}$$

$$d_{lights\_sine2} = s_{2\_lights\_HH} \times \text{sine}(2 \times \pi \times ((N_d - n)/N_y) - \varphi_{2\_lights\_HH}) \quad \textbf{[4-21]}$$

$$d_{lights\_sine} = d_{lights\_sine1} + d_{lights\_sine2} + k_{lights\_HH}$$

if $d_{lights\_max} \geq d_{lights\_sine} \geq d_{lights\_min}$,

$$d_{HH\_group\_lights} = d_{lights\_sine} + r_{lights\_sine\_HH} \quad \textbf{[4-22]}$$

if $d_{lights\_sine} > d_{lights\_max}$,

$$d_{HH\_group\_lights} = d_{lights\_max} + r_{lights\_max\_HH} \quad \textbf{[4-23]}$$

if $d_{lights\_sine} < d_{lights\_min}$,

$$d_{HH\_group\_lights} = d_{lights\_min} + r_{lights\_min\_HH} \quad \textbf{[4-24]}$$

if $d_{lights\_HH\_group} < 0$,

$$d_{HH\_group\_lights} = 0 \quad \textbf{[4-25]}$$

d_{lights_sine1}, d_{lights_sine2}, d_{lights_sine} are the normalised half-hourly, group averaged sinusoidal demand components for lighting appliances in a given half-hour on one of three day types

$s_{1\_lights\_HH}$, $s_{2\_lights\_HH}$ are the sine amplitude factors for the half-hour

n is the equivalent number of days by which sunrise and sunset are changed due to the clock changes, with n=0 from the change from GMT to BST (occurs at 02:00 on the last Sunday of March) until the change from BST to GMT (occurs at 02:00 on the last Sunday of October). Otherwise, n=34

$\varphi_{1\_lights\_HH}$, $\varphi_{2\_lights\_HH}$ are the sine phase angle

k_{lights_HH} is the sine constant

d_{lights_max}, d_{lights_min} are the maximum and minimum lighting demands for the half-hour (where relevant)

$r_{lights\_sine\_HH}$, $r_{lights\_max\_HH}$, $r_{lights\_min\_HH}$ are random number, selected from a normal distribution of zero mean and standard deviation of σ_{lights_sine}, σ_{lights_max} and σ_{lights_min} respectively.

and

$$D_{HH\_group\_lights} = d_{HH\_group\_lights} \times p_{lights} \qquad \textbf{[4-26]}$$

where:

$D_{HH\_group\_lights}$ is the demand (kW) for a specific half-hour for lighting appliances on one of three day types

p_{lights} is the estimated annual peak diversified demand for lighting appliances (kW) in a specific year

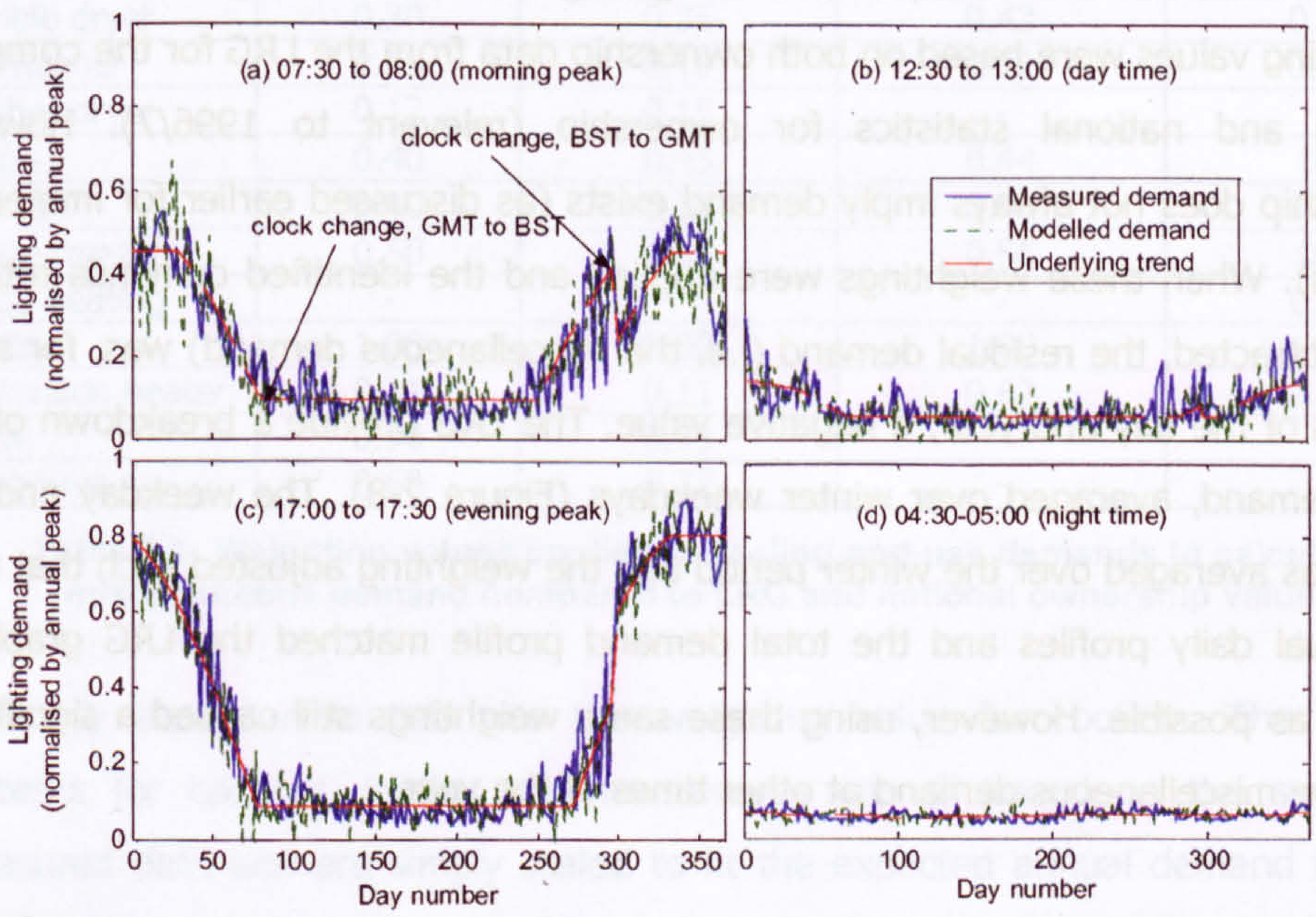


Figure 4-23: Annual pattern of demand for lighting showing dependence on time of day (normalised by diversified annual peak, half-hourly demand, group averaged. Based on LRG data 1996/7)

4.7 Miscellaneous demand – half-hourly, group averaged

The demands from all other domestic appliances are grouped together as miscellaneous demand, which in 1998 accounted for around 14% of the total annual domestic demand. Of this, approximately 3.6% is estimated to arise from televisions and videos, 3.3% from home office equipment and 1.8% to audio equipment [DEFRA, 2001].

The LRG dataset provides total half-hourly demand values for both unrestricted and Economy-7 tariffs for April 1996 to March 1997. To derive the miscellaneous component, it was necessary to subtract from the total demand the sum of demands arising from the appliances previously modelled. However, not all the households used for sampling the total demonstrated a demand for all of the identified end-uses – the sample sizes for the end-use and appliance data were generally much smaller (as described in Chapter 3, Table 3.1). It was necessary to develop a method of weighting the various end-use/appliance demands to represent the possible requirements of the group used for the total demand measurements.

Different methods were compared for weighting the various categories of demand. Weighting values were based on both ownership data from the LRG for the complete sample and national statistics for ownership (relevant to 1996/7). However ownership does not always imply demand exists (as discussed earlier for immersion heaters). When these weightings were applied and the identified demands totalled and subtracted, the residual demand (i.e. the miscellaneous demand) was, for some periods of the day and year, a negative value. The LRG provide a breakdown of the total demand, averaged over winter weekdays (Figure 2-8). The weekday end-use data was averaged over the winter period and the weighting adjusted such that their individual daily profiles and the total demand profile matched the LRG graph as closely as possible. However, using these same weightings still caused a significant negative miscellaneous demand at other times of the year.

To derive weightings that were realistic and yet gave a non-negative value for the miscellaneous demand, a crude sensitivity analysis was adopted. Initially all the weighting values for the end-uses were set to 1, implying that all households used to measure the total demand also contributed to the end-use datasets. This clearly gave a very significant negative demand at certain times of the year for the miscellaneous component. The weightings for each end-use were reduced in steps of 0.1 and the sensitivity of the minimum value (i.e. most negative value) for the annual set of miscellaneous demand was investigated. At each step, the three weighting values that caused the most significant change in the minimum demand value were reduced by 0.1 whilst the remainder were reset. Eventually the weightings were reduced until the negative miscellaneous demand was no more than 50W, which was considered a reasonable discrepancy (the vast majority of half-hourly values for miscellaneous demand were positive with negative values occurring almost exclusively at mid-day on Sundays in the summer months). Using this method gave weightings which were broadly in line with national statistics for ownership (Table 4-1).

Appliance/end-use	Final selected weightings	National figures (for ownership and usage)	LRG figures (for ownership of appliances within total sample group)	Weightings used for winter weekdays (to match LRG graph – Figure 2-8)
Cooker	0.10	0.62	0.55	0.55
Washing machine	0.70	0.76	0.94	0.8
Tumble dryer	0.30	0.35	0.43	0.45
Dishwasher	0.15	0.19	0.22	0.19
Washer dryer	0.12	0.15	-	-
Fridge	0.40	0.45	0.44	0.5
Freezer	0.40	0.58	0.46	0.46
Fridge-freezer	0.50	0.48	0.56	0.5
Space heating	-	-	-	0.05
Lights	1.00	1.00	1.00	1.00
Immersion heater	0.11	0.11	0.62	0.62
Kettle	0.90	0.99	-	-
Microwave	0.60	0.77	-	-

Table 4-1: Weighting values applied in scaling end-use demands to calculate miscellaneous demand compared to LRG and national ownership values

The only exception to this was the weighting value for cookers. The demand patterns for cookers, kettles and microwaves are all based on the same LRG measured data and are simply scaled to fit the expected annual demand for each appliance. This neglects any diversity in the use of cooking appliances and tends to over-estimate the contribution to the total demand, especially at mid-day on Sundays, when the measured cooking demand is highest. If the contributions for cookers, kettles and microwaves are recombined (taking account of the relative scaling factors for each), this suggests an ownership level of 0.51 for cookers – which is close to the LRG ownership level for cookers of 0.55. Whilst use of these weightings represents a compromise for estimating the miscellaneous component of demand, for most times of the day and year the assumptions are likely to be adequate. Since the use of off-peak tariffs is unlikely to affect the pattern of use for appliances in the miscellaneous category, the same demand pattern is used in the model for both unrestricted and Economy-7 consumers.

The calculated miscellaneous demand is modelled in a similar way to the other end-use/appliance categories, with different parameter values for four day types – Mondays, Saturdays, Sundays and other weekdays – to take account of the sensitivity of demand to day-type described earlier (Equationa 4-27 and 4-28, parameter values in Appendix B, section B.7). Miscellaneous demand shows a daily pattern, with peaks in the moming and mid-evening (Figure 4-24). The annual pattern of miscellaneous demand suggests a broadly inverse relationship to external ambient temperature and other weather factors (Figure 4-25), suggesting that miscellaneous demand includes a heating component.

$$d_{HH\_group\_misc} = s_{misc\_HH} \times \text{sine}(2 \times \pi \times (N_d/N_y) - \varphi_{misc\_HH}) + k_{misc\_HH} + r_{misc\_HH} \quad \textbf{[4-27]}$$

where:

$d_{HH\_group\_misc}$ is the normalised half-hourly, group averaged demand for miscellaneous appliances in a given half-hour on one of four day types

s_{misc_HH} is the sine amplitude factor for the half-hour

φ_{misc_HH} is the sine phase angle

k_{misc_HH} is the sine constant

r_{misc_HH} is a random number, selected from a normal distribution of zero mean and standard deviation of σ_{misc}

if $d_{HH\_group\_misc} < 0$, $d_{HH\_group\_lights} = 0$

and

$$D_{HH\_group\_misc} = d_{HH\_group\_misc} \times p_{misc} \quad \textbf{[4-28]}$$

where:

$D_{HH\_group\_misc}$ is the demand (kW) for a specific half-hour on one of four day types

p_{misc} is the estimated annual peak diversified demand for the wet appliance (kW) in a specific year

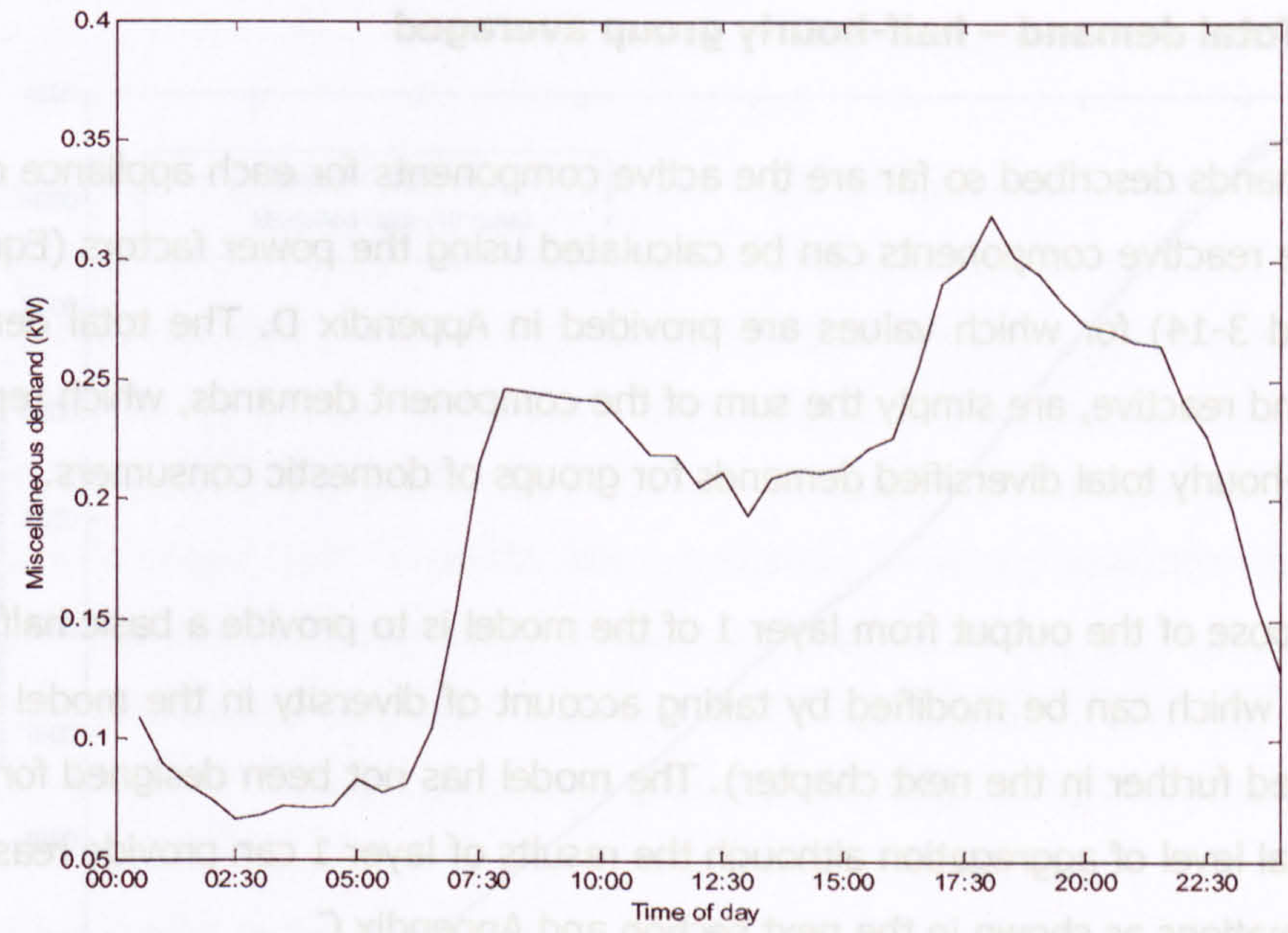


Figure 4-24: Daily pattern of demand for miscellaneous appliances (annual average, half-hourly demand, group averaged. Based on LRG data for 1996/7)

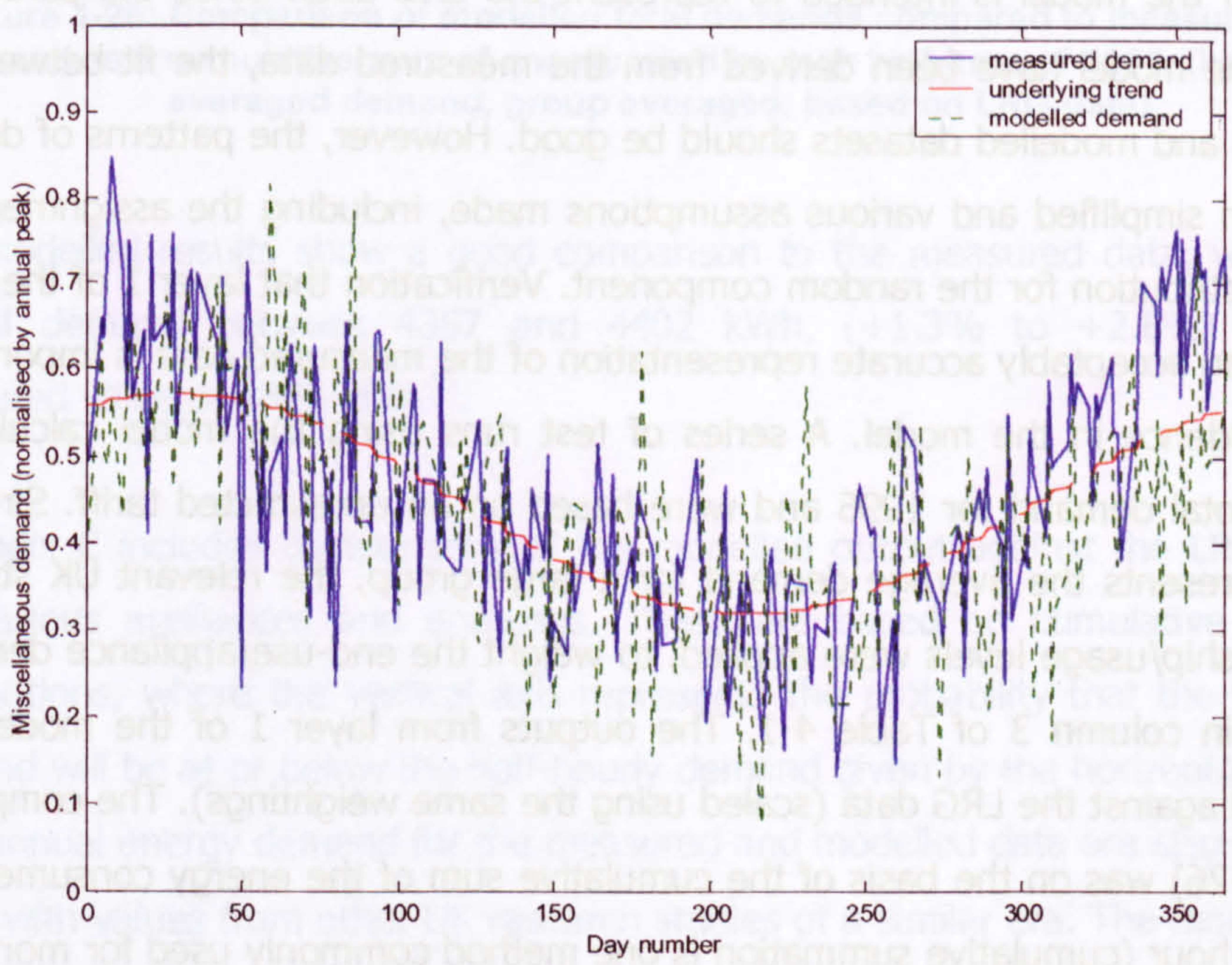


Figure 4-25: Annual pattern of demand for miscellaneous appliances between 18:00 to 18:30, weekdays (normalised by diversified annual peak, half-hourly demand, group averaged. Based on LRG data, 1996/7)

4.8 Total demand – half-hourly group averaged

The demands described so far are the active components for each appliance or end-use. The reactive components can be calculated using the power factors (Equations 3-13 and 3-14) for which values are provided in Appendix D. The total demands, active and reactive, are simply the sum of the component demands, which represent the half-hourly total diversified demands for groups of domestic consumers.

The purpose of the output from layer 1 of the model is to provide a basic half-hourly demand which can be modified by taking account of diversity in the model layer 2 (described further in the next chapter). The model has not been designed for use at a national level of aggregation although the results of layer 1 can provide reasonable approximations as shown in the next section and Appendix C.

4.9 Verification of layer 1 output

Layer 1 of the model is intended to represent the LRG data. Since the parameters used in the model have been derived from the measured data, the fit between the measured and modelled datasets should be good. However, the patterns of demand have been simplified and various assumptions made, including the assignment of a normal distribution for the random component. Verification that layer 1 of the model provides an acceptably accurate representation of the measured data is important to give confidence in the model. A series of test runs using the model calculated a notional total demand for 1996 and were based on an unrestricted tariff. Since the result represents the average demand for a large group, the relevant UK statistics for ownership/usage levels were applied, to weight the end-use/appliance demands, as given in column 3 of Table 4-1. The outputs from layer 1 of the model were compared against the LRG data (scaled using the same weightings). The comparison (Figure 4-26) was on the basis of the cumulative sum of the energy consumed over each half-hour (cumulative summation is one method commonly used for monitoring and testing energy consumption in buildings [Ferreira at al, 2003])

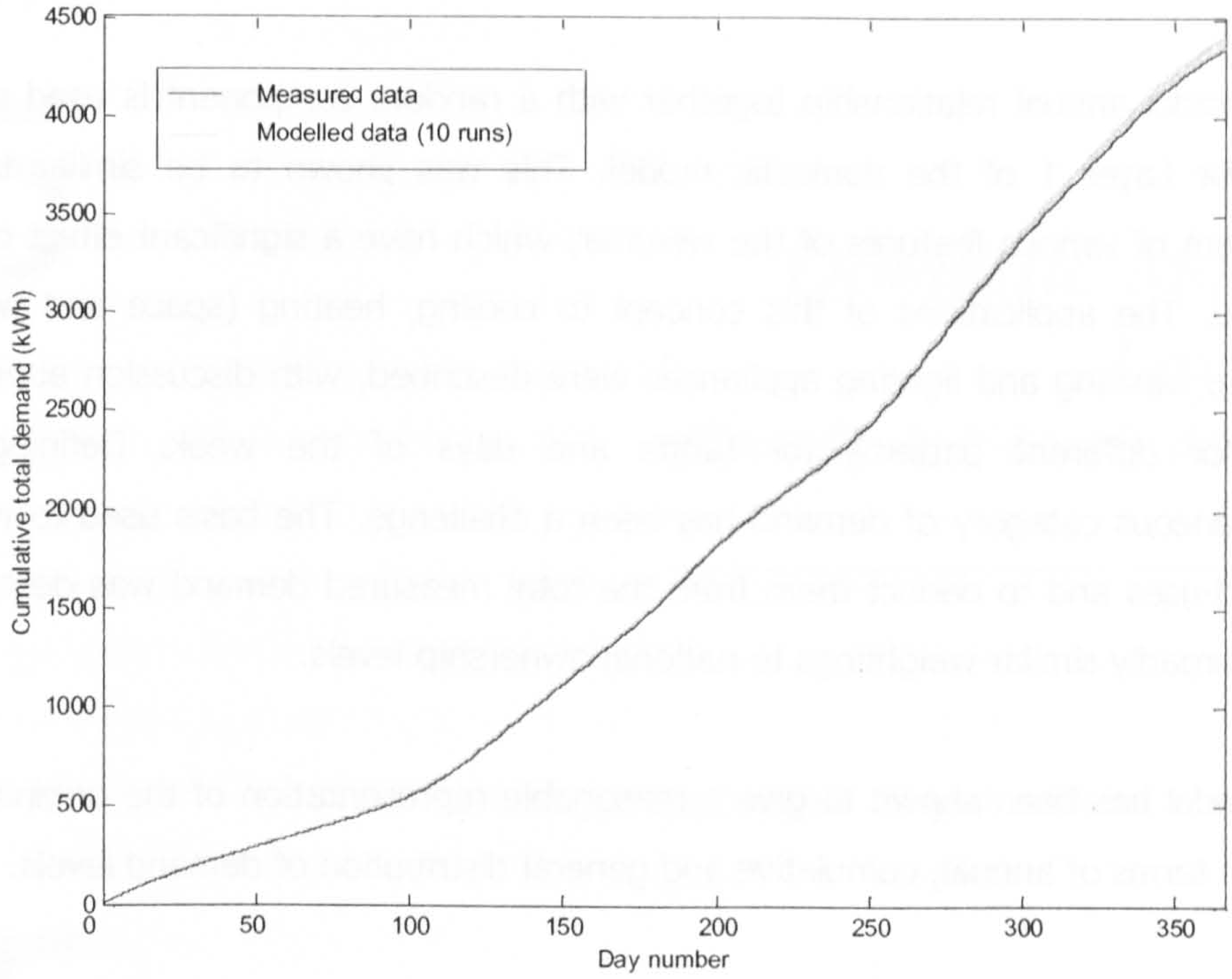


Figure 4-26: Comparison of modelled total demands compared to measured total demand as a cumulative sum of energy used in each half-hour of 1996. (half-hourly averaged demand, group averaged, based on LRG data)

The modelled results show a good comparison to the measured data, with a total annual demand between 4357 and 4402 kWh, (+1.3% to +2.8%) against a measured value of 4345 kWh [2] .

Appendix C includes comparisons of the modelled output against the LRG data for the various appliances and end-uses. These are based on cumulative frequency distributions, where the vertical axis represents the probability that the half-hourly demand will be at or below the half-hourly demand given by the horizontal axis. The total annual energy demand for the measured and modelled data are also compared, along with values from other UK research studies of a similar era. The modelled data appear to provide an adequate representation of the LRG dataset.

[2] Elsewhere the LRG report an average annual consumption of 4450 kWh for unrestricted consumers, which is considered to be 15% greater than the national average [Electricity Association, 1998(a)]).

4.10 Summary of chapter 4

A sinusoidal annual relationship together with a random component is used as the basis for Layer 1 of the domestic model. This was shown to be similar to the treatment of various features of the weather, which have a significant effect on the demand. The applications of this concept to cooling, heating (space and water), cooking, washing and lighting appliances were described, with discussion about the need for different patterns for tariffs and days of the week. Defining the miscellaneous category of demand has been a challenge. The basis used to weight the end-uses and to deduct them from the total measured demand was described, giving broadly similar weightings to national ownership levels.

The model has been shown to give a reasonable representation of the original LRG data, in terms of annual, cumulative and general distribution of demand levels.

Chapter

5

Domestic Model: Layer 2

(Specific, half-hourly demand)

Diversity is the one true thing we all have in common.
ANON

The practical operation of many systems and facilities we use depends on a high degree of diversity. Shopping for festivities, travelling during public holidays, buying fuel before tax rises... these are all examples of systems operating satisfactorily under normal conditions but beginning to fail when our demands are synchronised. For electrical networks, diversity is an essential feature of the system operation. Increased generation and changed network configuration (opening or closing switch points) are used to cope with the high levels of demand when diversity is low.

The previous chapter described layer 1 of the domestic model, which delivers an estimate of the demand when the diversity within a group of consumers has been taken into account. The second and third layers, which deliver point loadings on the LV network, endeavour to recreate individual demands by accounting for some of the elements of diversity. This chapter investigates factors that affect diversity of demand for domestic consumers at the half-hourly level and how these are introduced to the model for each of the appliance/end-use categories.

5.1 Factors that affect diversity

5.1.1 Buildings

Since weather factors are significant for estimating electricity demand, then the location (latitude and height above sea level) and orientation of a building can certainly influence the demand. The built form will also determine the potential loss of heat energy from a building and the year of construction will give an indication of the methods and materials adopted and the degree of insulation applied. Such factors are important inputs to many energy models that aim to predict the consumption per building. Models such as BREHOMES [Shorrock and Dunster, 1997] and tools such as NHER [Chapman, 1994] tend to concentrate on energy for space and water heating since these can be linked directly to the characteristics of an individual dwelling. However, in the UK, use of electricity for lighting and appliances is very significant (70% of the total annual domestic demand in 1998 [DEFRA, 2001]).

Research by the LRG into the effects of built form on lighting [Electricity Association, 1998(b)] revealed only a small variation in lighting demand between detached and semi-detached properties (less than 0.05kW on the averaged winter weekday). However, lighting demand in these buildings during the morning and evening peaks was almost double that from flats and maisonettes (a difference of around 0.15 kW). The LRG identified that household income and the number of rooms (typically related to the number of occupants) has a significant effect on demand and built form is not independent of these factors. The domestic model therefore ignores the effects of built-form on demand, using income or lifestyle classification instead.

The LRG research also investigated differences in lighting demand based on location (comparing Scotland and the North and South of England) [LRG, 1998]; these variations were relatively small. The LRG found that differences in the degree of cloud cover and the timing of sunrise and sunset tended to compensate in terms of the level of demand. The timing of the peak in lighting demand could vary by one half-hour between Scotland and Southern England but only at certain times of the year (spring and summer). Since all consumers on an LV network will be at a similar location, it is assumed for this model that such diversity is not an issue.

For energy modelling it is also common to divide the living space into zones – those that are frequently occupied, such as living rooms or kitchens and areas that are less frequently occupied (other than for sleeping) such as bedrooms. Knowing the relative proportion of these zones in a house could help introduce diversity associated with lighting and miscellaneous categories of demand as well as space heating.

Since detailed information on buildings is not always readily available, diversity arising from building related factors is largely ignored for this model. Built form and age are simply used to estimate the total living space, where such information is not available from the user or GIS map (it is also used in the random assignment of water heating). Built form is not a required user input to the model and is assigned randomly when unknown.

5.1.2 Occupant related factors

The number of people living in the home has a large impact on the household energy demand. The scale of the demand will vary with the number of people (e.g. size of refrigerators, number of televisions) and the probability of using an appliance will also be linked (e.g. more frequent use of washing machines). The DECADE project [Boardman et al, 1994] examined relationships between various end-use demands and the number of people living in a house. For example, cooking demand is almost doubled comparing dwellings occupied by single people and those housing couples. The increase for a third person is much smaller and for more than three the demand rises only slightly. The model uses these relationships from DECADE and other sources (and assumes similar patterns for other end-uses) to scale the group-averaged demand pattern. The number of occupants is determined from the floor area, unless the user has specific information, and is not a required input to the model. The occupancy level provides a significant part of the diversity introduced into layer 2.

Most end-use demand occurs when occupants are active within the home, (with the possible exception of cooling appliance demand or storage heating which operate relatively independently). Another important factor is therefore the profile of occupancy. Typical load profiles for partially unoccupied residences (called type A) and homes that are occupied throughout the day (type B) are provided in Agar and

Newborough's research [Agar and Newborough, 1998]. The current version of the model does not apply such profiles (a clear basis for applying these categories is not generally available and might not easily be assigned to specific connection nodes). However, it is a relatively trivial matter to introduce such profiles into the model for end-uses that relate directly to occupant activity – as a gate that allows demand to occur at certain times of the day or year.

Occupant age has been shown to be a significant factor in energy use. Homes including only elderly people tend to use more heat energy. Children use less energy per capita and hence families that include children of 5-15 will use less energy than the occupant/demand relationships would predict [Hitchcock, 1991]. Since distributions of the ages of occupants in a network area could be hard to identify, this factor of diversity is also ignored but could be introduced as a scaling factor if required.

Income and lifestyle rating have been found to significantly influence electricity demand. Simple relationships between demand and income have tended to elude researchers [Hitchcock, 1991]. The LRG investigated the effect of ACORN lifestyle classification and income on domestic lighting demand [Electricity Association, 1998(b)]. Not only was the demand significantly higher for those on larger incomes but also the daily demand pattern was different. The model adjusts lighting demand using this work as a basis. A further study [Mansouri et al, 1996] revealed variations in the ownership and use-patterns of several appliances in relation to income and lifestyle classification. When possible, this work has been incorporated in the load models.

ACORN classifications, which changed in 2000 to refine the category descriptions [CACI, 2004], provide are six basic lifestyle categories from A to F, with many, more detailed sub-categories (Table 5-1). These categories are widely available for postcode areas and are used within the model[1].

[1] Some older research studies tend to use the National Readership Survey (NRS) social grade definitions A, B, C1, C2, D and E based on assumed class boundaries. Whilst the two lifestyle classifications are not entirely compatible, it is assumed for this model that the six categories in the NRS systems are equivalent to those used for the ACORN classification.

ACORN types	ACORN groups
A-thriving	• wealthy achievers, suburban areas • affluent greys, rural communities • prosperous pensioners, retirement areas
B- expanding	• affluent executives, family areas • well-off workers, family areas
C- rising	• affluent urbanites, town and city areas • prosperous professionals, metropolitan areas • better-off executives, inner city areas
D – settling	• comfortable middle agers, mature home owning areas • skilled workers, home owning areas
E – aspiring	• new home owners, mature communities • white collar workers, better-off multi-ethnic areas
F - striving	• older people, less prosperous areas • council estate residents, better-off homes • council estate residents, high unemployment • council estate residents, greatest hardship • people in multi-ethnic low income areas

Table 5- 1: ACORN classifications in terms of types and groups

All of these occupant related diversity factors described in this section can influence demand in various ways. Diversity relates to ownership – whether appliances are owned, how many and in what combinations. It derives from variety in the scale of demands – related to how many people are served by an appliance. It arises in patterns of use – timing and frequency. Finally the efficiency with which an appliance operates affects the demand. The latter is incorporated into this model in the next layer but the other factors are accounted for here. The challenge at this stage is to consider how each end-use is affected by the issues of ownership, scale and pattern of use and how these may be represented in order to introduce diversity. The sections that follow provide further explanation for each category.

5.2 Cooling demand – half-hourly, specific

5.2.1 Ownership of cooling appliances

Ownership of refrigerators peaked in 1975 but has been falling since as combined fridge-freezers have become more popular. Current UK levels for ownership are around 43% for refrigerators and 65% for fridge-freezers [DEFRA,2001]. Similarly ownership of freezers has become more common since the 1970s although levels have now reached a plateau, with around 28% of UK homes owning either a chest or upright freezer [DEFRA, 2001].

It is common for more than one cooling appliance to be owned and Mansouri et al's study provides statistics for various combinations of ownership [Mansouri et al, 1996]. This research has been interpreted for use in the domestic model (Appendix D, Section D.1).

5.2.2 Effect of occupancy on cooling demand

Since little research data were available to link demand from cooling appliances with the number of occupants per household, a crude relationship has been evaluated based on LRG data showing the total daily demand profiles (averaged over Winter weekdays) for different occupant numbers (Figure 2-7). Since much of the demand at night-time is likely to arise from cooling appliances, the relative levels of demand in the early hours have been used to build a simple relationship between appliance demand and occupancy (Figure 5-1). The cooling demands from layer 1 are simply scaled according to the estimated occupancy at each connection point of the network, assuming the average occupancy to be 2.4.

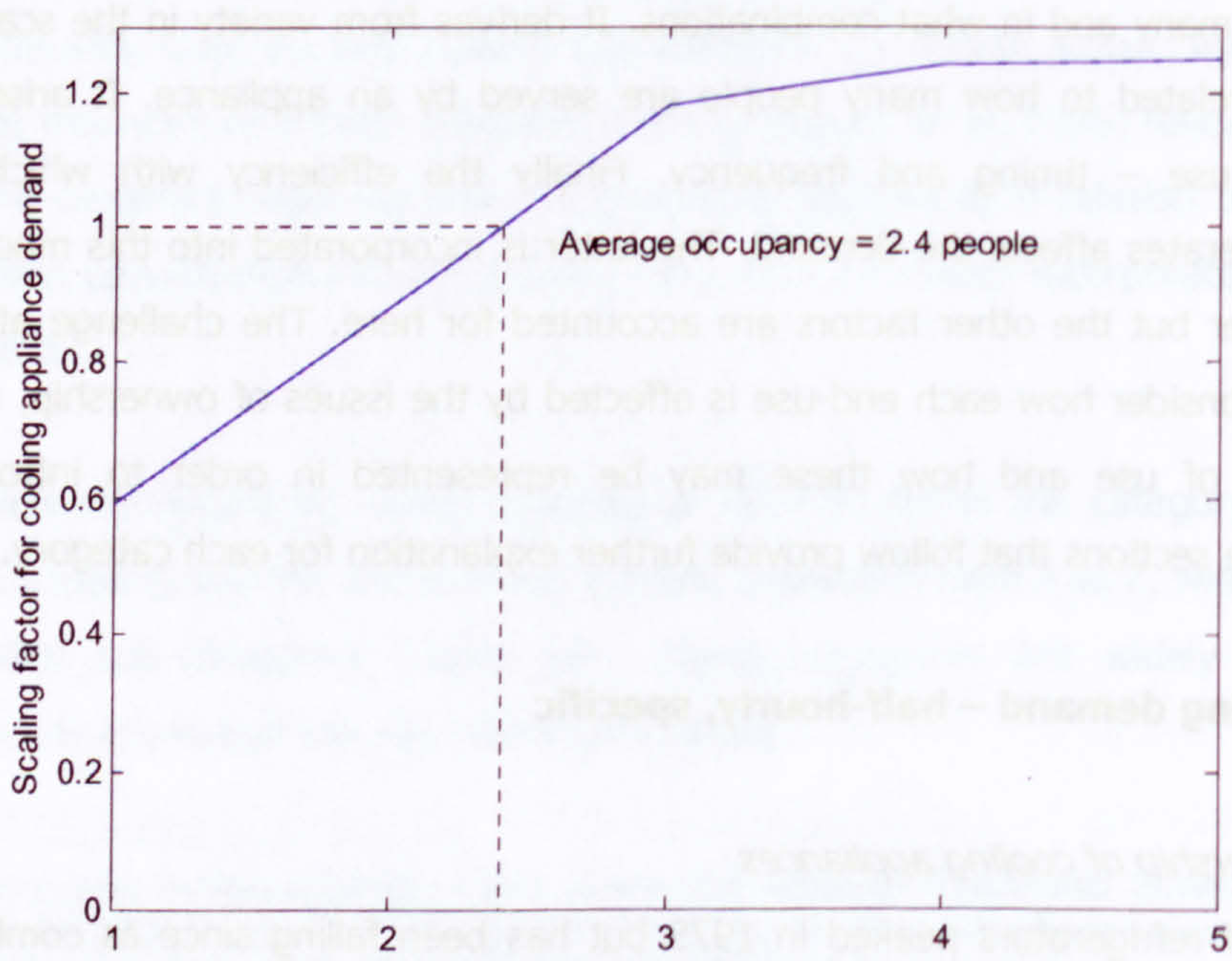


Figure 5-1: Assumed relationship between cooling appliance (refrigerators and fridge-freezers) demand and occupancy

This relationship is similar to that used for other end-uses and is applied in the model for refrigerators and fridge-freezers. Requirements for freezing capacity can be somewhat different (e.g. relatively small households might have large freezers for storage of pet food or bulk frozen purchases). The demand for freezing is randomly scaled, using a normal distribution with a mean of 1 and standard deviation of 0.316 (derived from the demand ratings for a sample of freezer units currently retailed).

5.2.3 Description of cooling demand for layer 2

Refrigeration demand (and similarly fridge-freezer and freezer demand) is calculated using equation 5-1 (values for parameters appear in Section D.1, Appendix D)

$$D_{HHspecific\_fridge} = D_{HHgroup\_fridge} \times k_{own\_fridge} \times k_{occ\_fridge} \qquad \textbf{[5-1]}$$

where:

$D_{HHspecific\_fridge}$ is the half-hourly demand assigned to a specific consumer

$D_{HHgroup\_fridge}$ is the group-averaged half-hourly demand (Equation 4-2)

k_{own_fridge} is a Boolean factor (= 0 if refrigerator not assigned, = 1 if refrigerator is assigned)

k_{occ_fridge} is a scaling factor depending on occupancy

5.3 Space heating demand – half-hourly, specific

5.3.1 Ownership of electric space heating

Since 1985, the ownership of electric space heating has remained relatively constant at about 10% of homes [DEFRA, 2001]. However, the 2001 English House Condition Survey (EHCS, [ODPM, 2001]) suggests that only 1% of central heating (assumed to be off-peak storage heating) is fuelled by electricity in England. Within the model, ownership can be assigned randomly over the network although it is more realistic for the user to select the heating method for the network area as a whole since this is very dependent on the availability of a gas supply. Use of electric storage heaters is more common in high-rise flats and local housing association dwellings [Wright, 1997]. Other variations have been observed in the relationship between electric heating appliances and built form [Gadsden, 2001]. These have not been used in the model although the user could choose to allocate use of electric heating to specific groups of consumers within the network area if required. The model only allows for electric storage heating (other heaters would be included in the miscellaneous demand) and thus it is assumed that all consumers with electric space heating would use an off-peak tariff.

5.3.2 Effect of living space on electric space heating

For the intended application in the Solar City tool, it is assumed that no information about the building at each connection point is provided from the GIS other than the floor area. Since floor area is likely to be related to heating demand, this is used to scale the demand pattern from layer 1. The demand is multiplied by the ratio of the total floor area of the dwelling to an averaged floor area of 87 m^2, taken from the EHCS 2001 [ODPM, 2001].

5.3.3 Description of space heating demand for layer 2

Space heating demand is calculated using equation 5-2 (values for parameters appear in Section D.2, Appendix D)

$$D_{HHspecific\_heat} = D_{HHgroup\_heat} \times k_{own\_heat} \times k_{occ\_heat} \qquad \textbf{[5-2]}$$

where:

$D_{HHspecific\_heat}$ is the half-hourly demand assigned to a specific consumer

$D_{HHgroup\_heat}$ is the group-averaged half-hourly demand (Equation 4-12)

k_{own_heat} is a Boolean factor (= 0 if space heating not assigned, = 1 if space heating is assigned)

k_{occ_heat} is a scaling factor depending on floor area (compared to mean floor area of $87m^2$)

5.4 Water heating demand – half-hourly, specific

5.4.1 Ownership of electric water heating

Assigning ownership of immersion water heating is complicated since many homes own an immersion heater although relatively few use them. The MTP [DEFRA, 2001] identified two groups of users – those using immersion water heating all year round and those who use electric water heating in the summer months only (assumed in this model to be from June to September inclusive), often when gas or solid fuel boilers, which also provide space heating, are not in use. Trends in ownership for summer or all year round use, based on the MTP data, are provided in Appendix D, section D.3.

If specific information is unknown, the model assigns ownership of immersion heaters on a random basis, using the current national statistic (currently around 61% [DEFRA, 2001]). Within the group of owners, use patterns are also randomly assigned to give all year round demand (26% of owners), summer only demand (around 15% of owners) or non-use. It is assumed that homes with electric space heating using an off-peak tariff will also use immersion water heaters at off-peak times throughout the year.

5.4.2 Effect of built form on ownership of electric water heating demand

Use of electricity as a fuel for water heating has been found to be dependent on built form with greater use in flats (28% of homes) but is relatively less common in older properties (11% of homes, pre-1980 and 18% post 1980 [ODPM, 2001]). These data are incorporated in the demand model by applying a weighting factor (Appendix D, section D.3.3) to the levels of ownership before the random assignment.

5.4.3 Effect of occupancy on electric water heating demand

Hot water demand varies depending on the number of people in a house. The relationship given by the BREDEM-8 model identifies a fixed and variable component (Equation 5-3).

Hot water demand (litres/day) = 38 +(25 x N) **[5-3]** where N is the number of occupants and can be calculated from the BREDEM standard occupancy formulae (Equations 3-7 and 3-8). Assuming an average household occupancy of 2.4 people, the model adopts values to scale the demand for electrical water heating, based on the number of people within a household (Figure 5-2 with values given in section D3.4 of Appendix D).

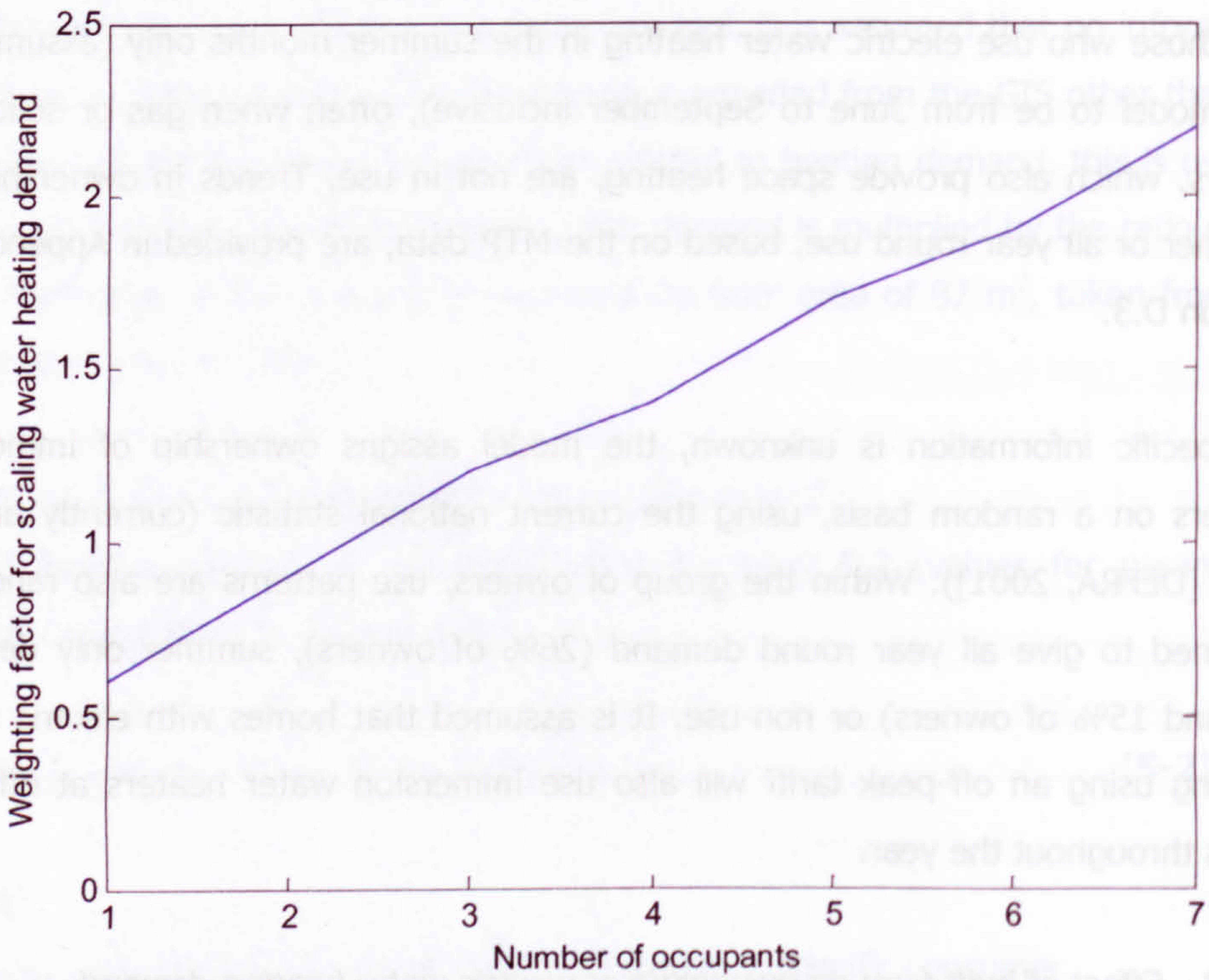


Figure 5-2: Values used for scaling water heating demand in relation to occupancy

Additionally, adjustments are made on a random basis to account for high, average, low and very low levels of demand using an assumed distribution of 12%, 75%, 12% and 2%, based on the BREDEM-8 model. The scaling factors for this adjustment also appear in Appendix D, section D3.5.

5.4.4 Description of water heating demand for layer 2

Water heating demand is calculated using equation 5-4 (values for parameters appear in Section D.3, Appendix D)

$$D_{HHspecific\_water} = D_{HHgroup\_water} \times k_{own\_water} \times k_{occ\_water} \times k_{hi\text{-}lo\_water} \qquad \textbf{[5-4]}$$

where:

$D_{HHspecific\_water}$ is the half-hourly demand assigned to a specific consumer
$D_{HHgroup\_water}$ is the group-averaged half-hourly demand (Equation 4-15)
k_{own_water} is a Boolean factor (= 0 if water heating not assigned, = 1 if all-year water heating is assigned or =1 only between June to September inclusive if summer-only water heating is assigned)
k_{occ_water} is a scaling factor depending on number of occupants
$k_{hi\text{-}lo\_water}$ is a scaling factor that depends of random selection of high, average, low or very low water usage

5.5 Cooking demand – half-hourly, specific

5.5.1 Ownership of electric cooking appliances

Built-in cooking appliances have provided the opportunity for the use of different fuels for specific tasks. Increasingly in the UK, gas is the preferred fuel for hob cooking and electricity for cooking in an oven. Ownership of electric ovens is increasing (currently around 65% of homes [DEFRA, 2001]) whilst ownership of electric hobs is predicted to fall slowly (currently at around 47%). Cooking with fuels other than electricity or gas is becoming rare. For the purposes of this model, if a specific dwelling is assigned electric storage heating, it is also assumed that cooking will be by electricity. Further, the model also assumes that since gas has become the preferred choice of fuel for hobs, assignment of an electric hob implies ownership of an electric oven. Trends in the ownership figures for electric hobs and ovens, based on MTP data [DEFRA, 2001], as used in the model are provided in Appendix D, section D.3.

Ownership of electric kettles (assumed to be around 99%) and microwaves (currently approximately 85%) is relatively stable and expected to remain so. Consequently no trend data are used for assigning ownership of these appliances. Microwave ownership has been found to vary with lifestyle category [Mansouri et al, 1996], with significantly higher levels of ownership in the C2 group (NRS's lower middle class category, assumed equivalent to ACORN's 'settling' type). Mansouri's distribution of ownership in relation to lifestyle category is used to vary the current national statistic in the model (Appendix D, D.3). For all cooking appliances, unless the user has specific information (or rules for combination with other end-uses apply), ownership is assigned randomly in line with the current national statistics (varied by lifestyle category for microwaves) over the consumers in the network area.

5.5.2 *Effect of occupancy on cooking demand*

The BREDEM-8 model identifies a relationship between the annual energy use for cooking and the number of occupants in a home (Equation 5-5).

$$E_k = 1.70 + 0.34 * N \qquad \textbf{[5-5]}$$

where:

E_k is annual cooking fuel used (GJ/year)

N is the number of occupants

The DECADE report [Boardman et al, 1994] suggests that whilst cooking demand virtually doubles when the number of occupants increases from one to two, the demand remains fairly stable as the size of a household increases further, especially for three or more people. For this model, the cooking demand from layer 1 is scaled by values based on the DECADE data (Figure 5.3, values provided in Appendix D, D4.3).

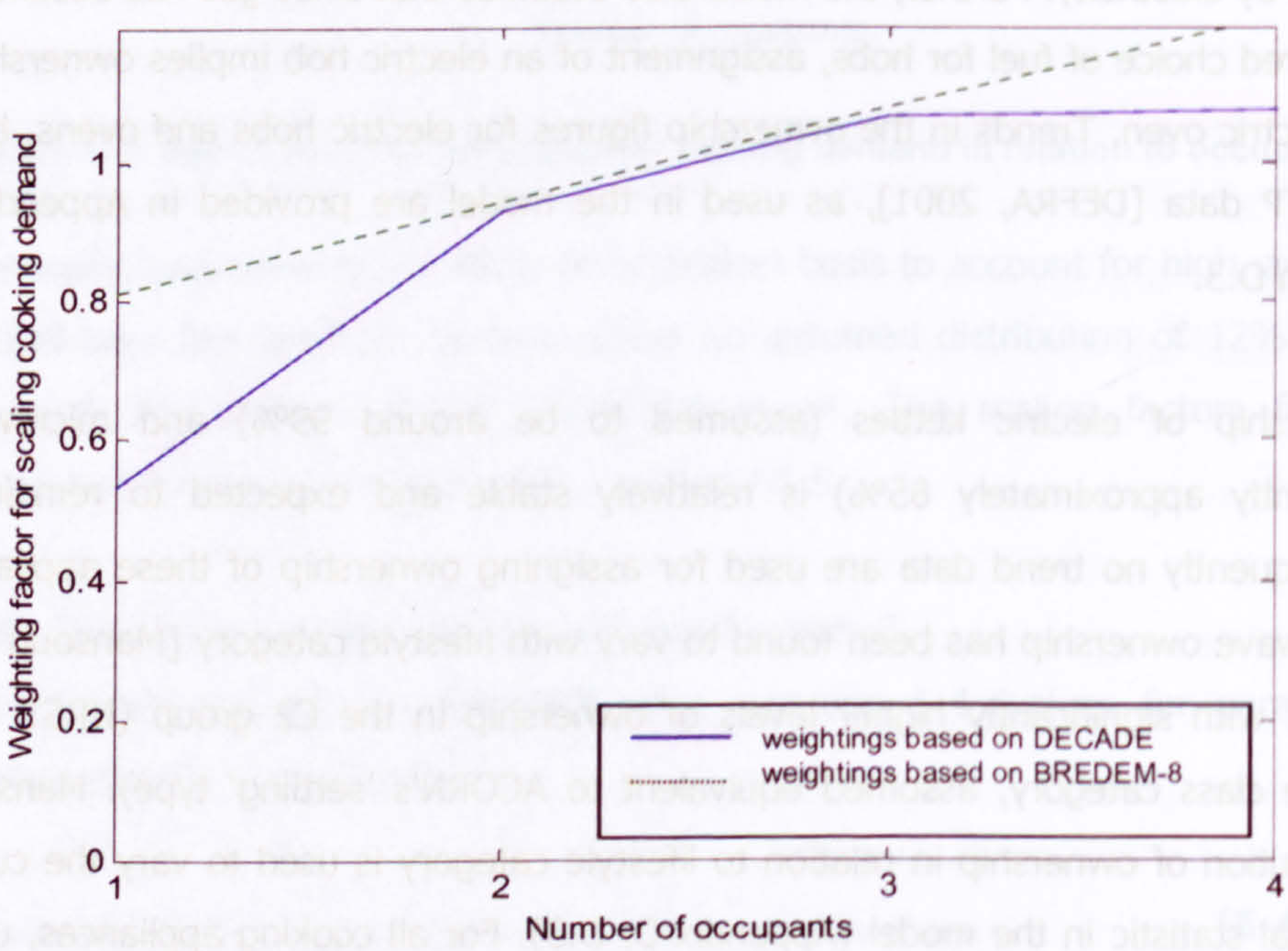


Figure 5-3: Values used for scaling cooking appliance demand in relation to occupancy

5.5.3 *Description of cooking demand for layer 2*

Cooking (whether hob, oven, kettle or microwave) demand is calculated using equation 5-6 (values for parameters appear in Section D.4, Appendix D)

$$D_{HHspecific\_cook} = D_{HHgroup\_cook} \times k_{own\_cook} \times k_{occ\_cook} \qquad \textbf{[5-6]}$$

where:

$D_{HHspecific\_cook}$ is the half-hourly demand assigned to a specific consumer

$D_{HHgroup\_cook}$ is the group-averaged half-hourly demand (Equation 4-17)

k_{own_cook} is a Boolean factor (= 0 if cooking appliance not assigned, = 1 if cooking appliance is assigned)

k_{occ_cook} is a scaling factor depending on number of occupants

5.6 Wet appliance demand – half-hourly, specific

5.6.1 *Ownership of wet appliances*

The MTP research [DEFRA, 2001] is used to provide ownership data for washing appliances in this model. Washing machine ownership has increased since the 1970s but is now virtually stable in the UK at levels of around 76%. Similarly ownership of tumble dryers increased from a low base level throughout the 1980s but the market became saturated with current levels of around 35%. Ownership does depend on socio-economic groups. In one study [Mansouri et al, 1996] 71% of people in the C2 NRS group (assumed ACORN's 'settling' type D) owned tumble dryers compared to just 45% in E group households (assumed ACORN's 'striving' type F). These lifestyle variations in ownership of washing machines and tumble-dryers are used in the model but adjusted to follow the levels and annual trends in the MTP data (Appendix D, Section D.5)

Dishwasher ownership has also increased rapidly since becoming available in the 1970s. The MTP [DEFRA, 2001] estimated that nationally, around one third of UK homes own one. The 1992 Regional Trends data [HMSO, 1992] suggested that ownership of dishwashers showed strong regional variations, with ownership levels in Greater London and the southern and eastern regions of England almost double that in other areas of the UK. These regional variations are not implemented directly within the model but could be introduced by the user for specific locations as required. Mansouri et al's sample showed far higher levels of ownership and also revealed variations in dishwasher ownership in relation to lifestyle indicator, with highest levels in the A/B categories (57%) and lowest in the NRS E group (assumed ACORN's type F) households (36%). These are used in the model for random assignment but adjusted in accordance with the MTP data trends.

Finally, ownership of combined washer-dryer appliances has reached saturation at around 15% for UK homes. The MTP report that roughly 15% of homes owning these combined appliances also have a tumble-dryer. Since ownership of both a washing machine and a combined washer-dryer is unlikely, the model assigns either one or the other using national statistics (adjusted by social category if applicable) which suggest that currently around 92% of homes have access to some kind of washing appliance.

5.6.2 Tariff assignment for wet appliance demand

Layer 1 of the model provides the averaged demand patterns for consumers using wet appliances on an unrestricted or off-peak (Economy-7) tariff. In layer 2 tariff assignment is random, based on national or local statistics (with automatic assignment of an off-peak tariff for consumers using electric space heating). Whilst no specific statistics have been found regarding the number of off-peak consumers in the UK, if households using electricity for water heating throughout the year are also assumed to be off-peak consumers, the figure is likely to be around 25%.

5.6.3 Effect of occupancy on wet appliance demand

Although wet appliances tend to be of standard sizing and not selected in relation to the number of people in a household, the frequency of use is dependent. Since the demand assigned for the second layer of the model is later used as a probability that a demand event takes place, an appropriate scaling factor in relation to household size is used at this point in the model. Mansouri et al's study showed that the number of wash cycles per week depended both on the number of people and the mix of adults and children. The latter distinction is considered too detailed for this model although using Mansouri et al's data for the numbers of wash cycles per week, an occupancy/demand relationship for both washing and drying appliance demand has been incorporated into the model (Figure 5-4, Appendix D, Section D.5). No occupancy factor has been included for dishwasher demand; it has been assumed that the frequency of use for a dishwasher is determined by mealtimes and the appliance used regularly whether full or not. In Mansouri et al's sample, over half used a dishwasher once per day with 34% using one every two days.

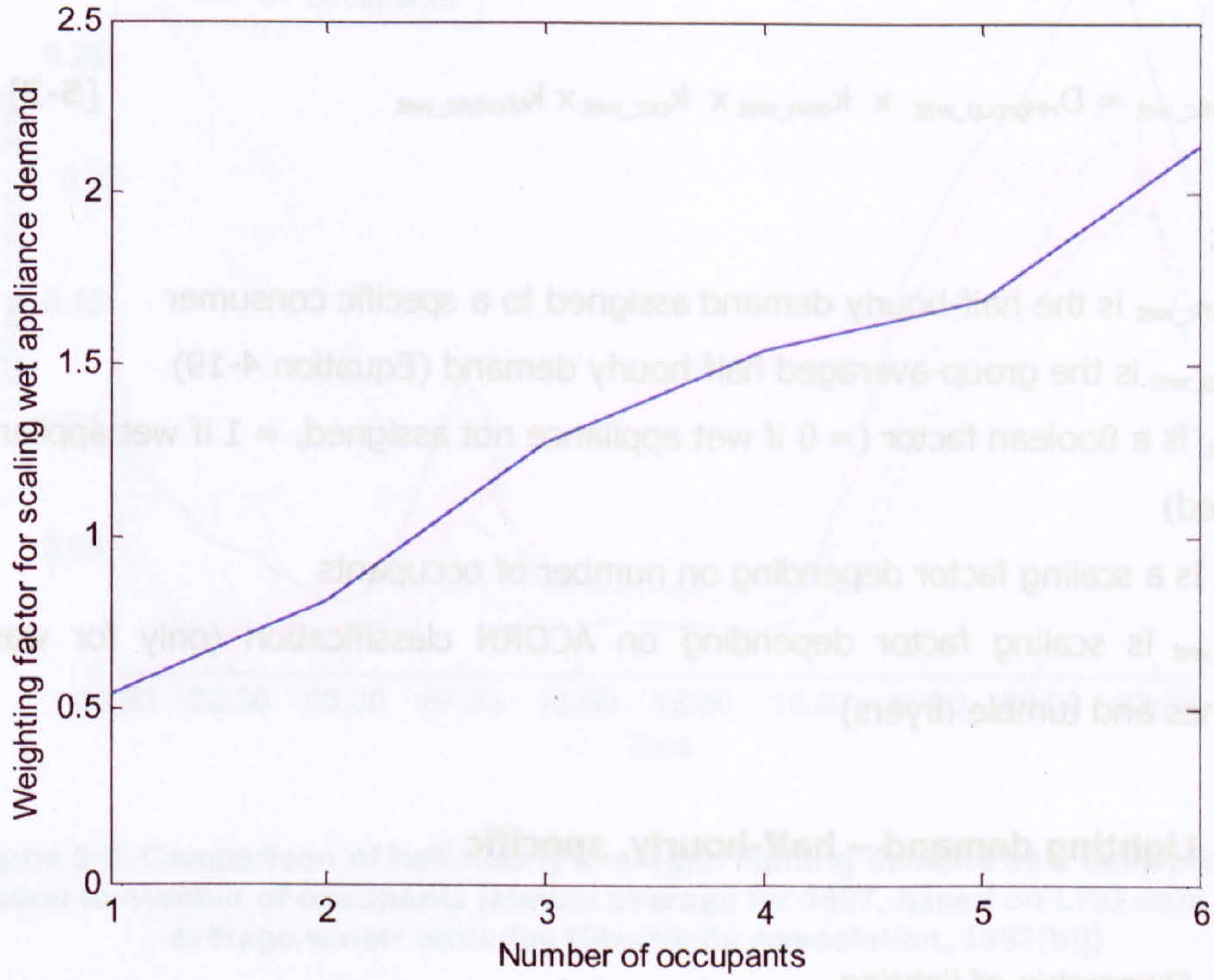


Figure 5-4: Values used for scaling wet appliance demand in relation to occupancy (based on [Mansouri et al, 1996])

5.6.4 Effect of lifestyle factor on wet appliance demand

The study also provided a breakdown of the average number of washing and drying events per week based on the NRS lifestyle factor. Households in group C2 (assumed ACORN's 'settling' type D) had the highest number of wash cycles per week (average 8.0) compared to those in group C1 (assumed ACORN's 'rising' type C, average 4.8). Those in group D (assumed ACORN's 'aspiring' type E) used a tumble dryer almost twice as often as the average (4.2 drying events per week compared to an average of 2.11). The effect of lifestyle has been incorporated as a scaling factor that adjusts the levels of demand for washing and drying appliances (Appendix D, Section D.5). Since the variation in use of dishwashers is small across the lifestyle categories (0.8 to 0.88 cycles per day), no similar scaling factor is applied to diversify dishwasher demand.

5.6.5 Description of washing demand for layer 2

Washing (whether washing machine, tumble dryer or dishwasher) demand is calculated using equation 5-7 (values for parameters appear in Section D.5, Appendix D)

$$D_{HHspecific\_wet} = D_{HHgroup\_wet} \times k_{own\_wet} \times k_{occ\_wet} \times k_{lifestyle\_wet} \qquad \textbf{[5-7]}$$

where:

$D_{HHspecific\_wet}$ is the half-hourly demand assigned to a specific consumer

$D_{HHgroup\_wet}$ is the group-averaged half-hourly demand (Equation 4-19)

k_{own_wet} is a Boolean factor (= 0 if wet appliance not assigned, = 1 if wet appliance is assigned)

k_{occ_wet} is a scaling factor depending on number of occupants

$k_{lifestyle\_wet}$ is scaling factor depending on ACORN classification (only for washing machines and tumble dryers)

5.7 Lighting demand – half-hourly, specific

5.7.1 Ownership of lighting

Homes that use fuels other than electricity for lighting are extremely rare. This model assumes that every domestic consumer will provide a lighting demand on the LV network.

5.7.2 Effect of occupancy on lighting demand

LRG research into lighting demand [Electricity Association, 1998(b)] revealed that occupancy had a considerable impact. Annual lighting demand for households with four or more people was over 80% higher than that for single occupant homes. Not only is the scale of demand affected but the daily pattern varies as well. The model uses scaling factors for each half-hour of the day based on the LRG's findings for the averaged winter weekday in relation to the number of occupants (Figure 5-5, Section D.6, Appenidx D).

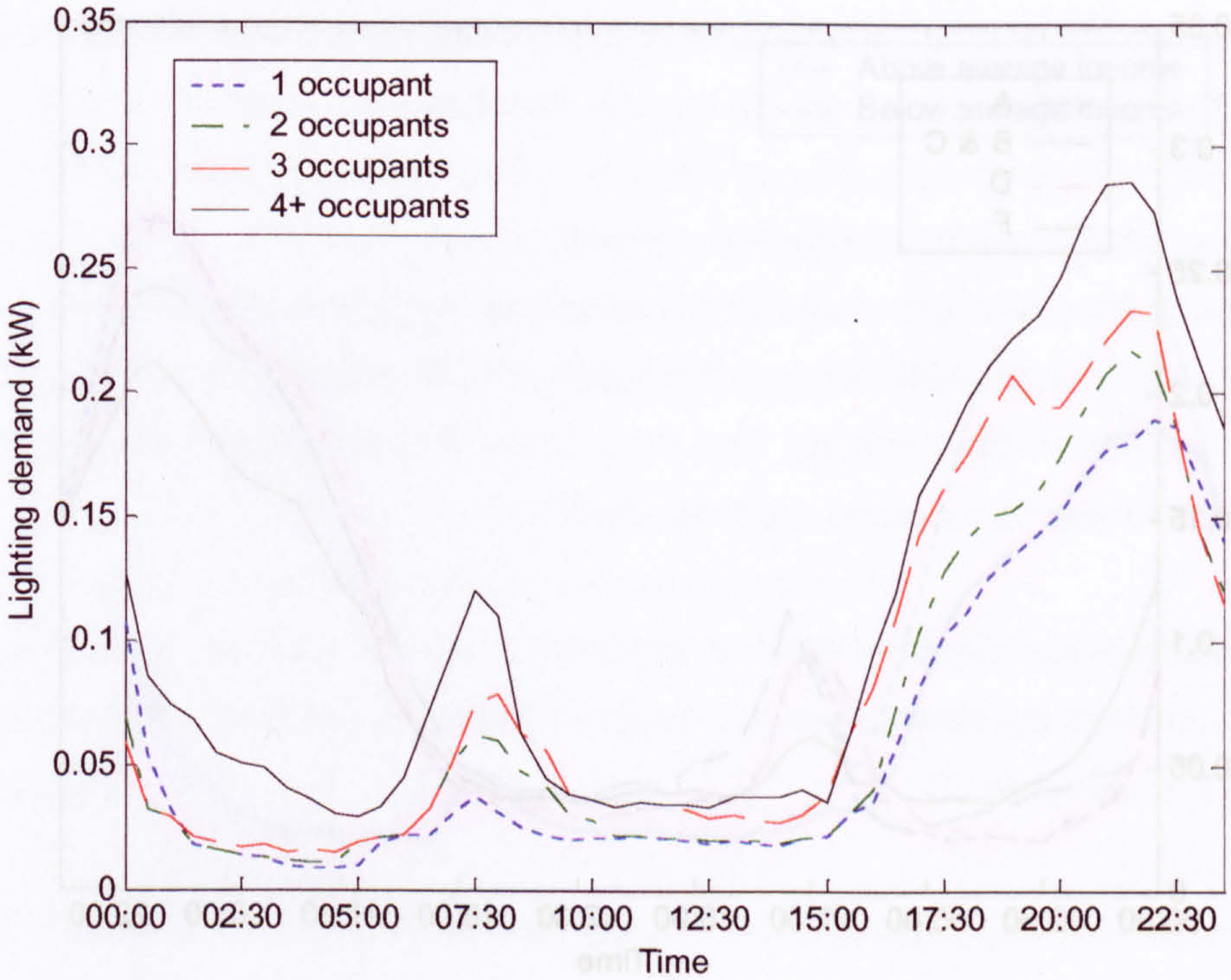


Figure 5-5: Comparison of half-hourly averaged lighting demand as a daily profile in relation to number of occupants (annual average for 1997, based on LRG data for the average winter weekday [Electricity Association, 1998(b)])

These data suggest that the night-time demand in larger households is much higher than average, although the demand is still at a very low level. The early evening peak in demand is more accentuated in homes with three or more occupants.

5.7.3 Effect of lifestyle classification on lighting demand

The LRG also investigated lighting demand based on ACORN lifestyle classification. It was found that lifestyle category did little to affect lighting demand apart from those in group F (described as 'Striving'), who showed lower demand during the morning and evening peaks but a higher night-time demand. The model uses lifestyle classification as a basis for scaling all half-hourly demands, using these findings, which are based on winter weekday averages (Figure 5-6, Section D.6, Appendix D).

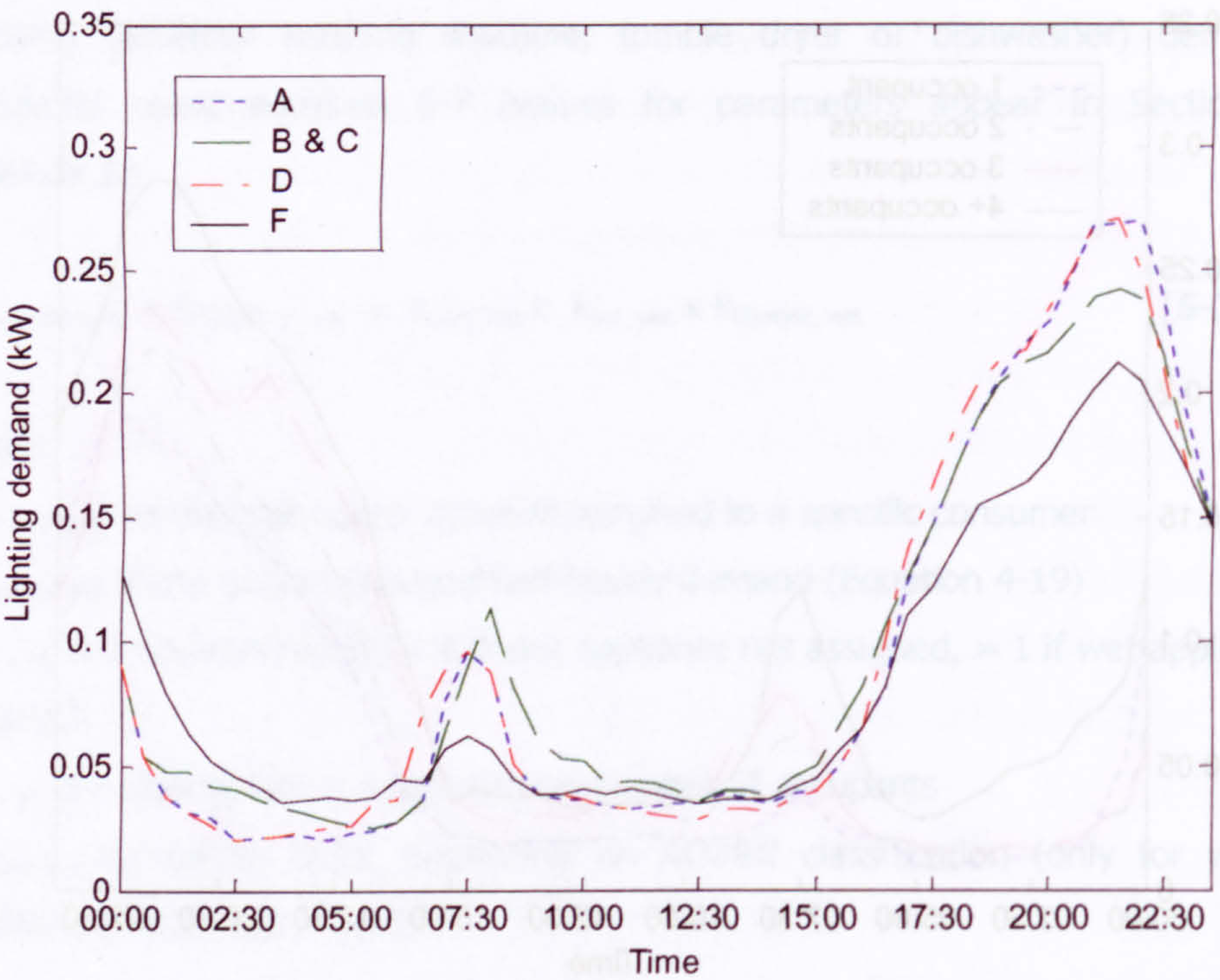


Figure 5-6: Comparison of half-hourly averaged lighting demand as a daily profile in relation to ACORN lifestyle category (annual average for 1997, based on LRG data for the average winter weekday [Electricity Association, 1998(b)])

5.7.4 Effect of income on lighting demand

The LRG lighting survey also found a strong relationship between income and lighting demand both in scale and pattern. The annual consumption is 40% greater for consumers with incomes above the national average (taken as £20,000 per annum at the time of the survey), with much higher morning and evening peak demands.

Since lifestyle classification and income are likely to be highly related, the model uses income information where this is available in preference to lifestyle indicator. However, since the ACORN ratings are widely available for postcode areas, these are used within the model when income is unknown. Whilst the LRG reported the effect of income on the averaged winter weekday, the same values are used to scale all daily profiles in the model (Figure 5-7, Section D.6, Appendix D).

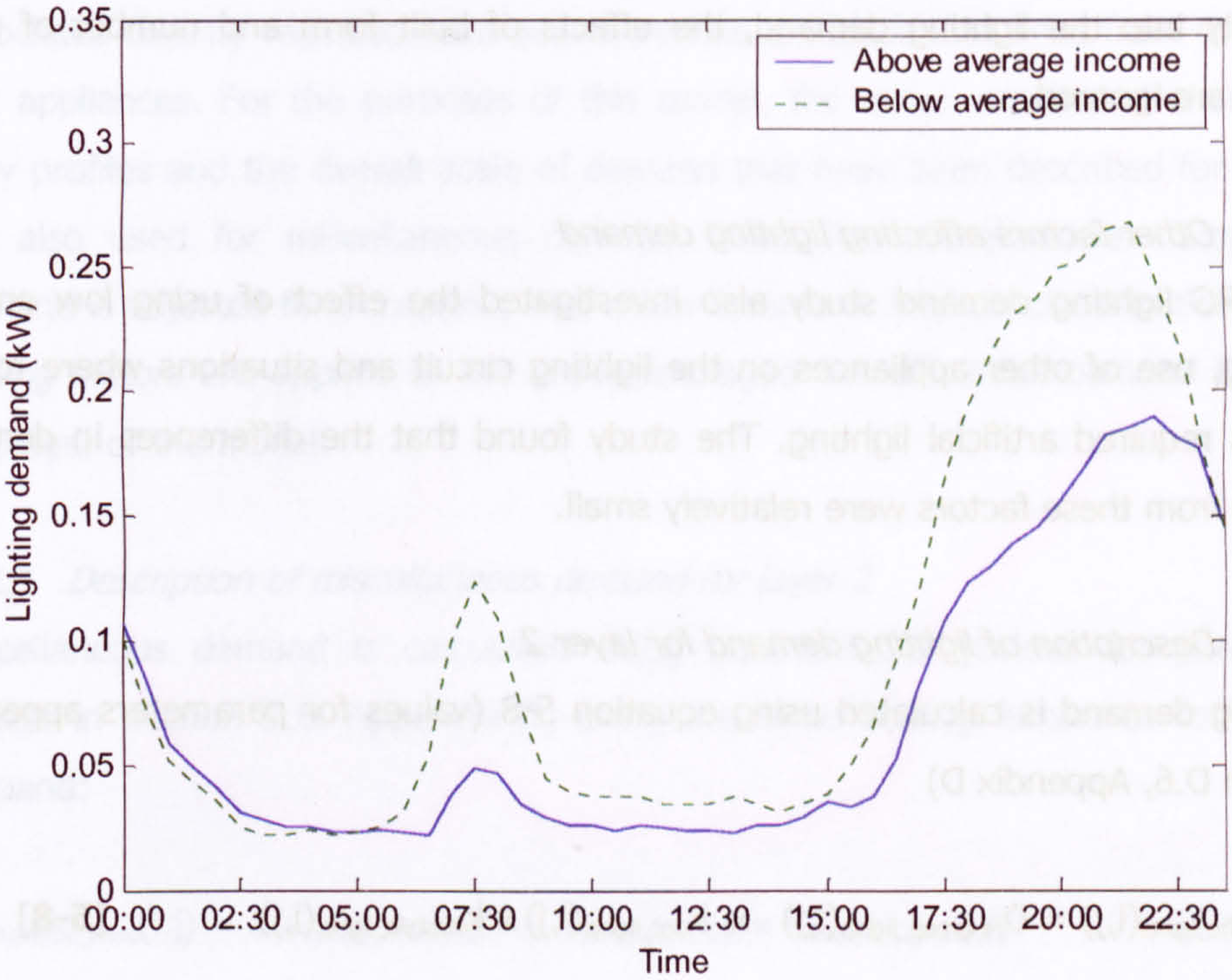


Figure 5-7: Comparison of half-hourly averaged lighting demand as a daily profile in relation to income (annual average for 1997, based on LRG data for the average winter weekday [Electricity Association, 1998(b)])

Average income is taken to be the current national average total household income and households with an income close to this average value are assigned an un-scaled lighting demand pattern as generated by layer 1 of the model.

5.7.5 Effect of built form and number of main rooms on lighting demand

The same survey showed that whilst consumers in semi-detached and detached properties had very similar lighting demand levels and patterns, those living in flats and maisonettes use less lighting during the morning peak time and have a much flatter demand at night. The number of main rooms was also a strong factor in determining both annual consumption and the daily demand patterns. The LRG report that homes with over eight main rooms use 80% more energy for lighting than homes with five and exhibit increased levels over much of the average winter weekday, especially at peak times.

The LRG highlights that many of these influences are not independent and that dwelling type, income and number of rooms are all linked. Since the model uses occupancy (based on floor area), income and lifestyle classification to introduce diversity into the lighting demand, the effects of built form and number of main rooms are ignored.

5.7.6 Other factors affecting lighting demand

The LRG lighting demand study also investigated the effect of using low energy lighting, use of other appliances on the lighting circuit and situations where rooms always required artificial lighting. The study found that the differences in demand arising from these factors were relatively small.

5.7.7 Description of lighting demand for layer 2

Lighting demand is calculated using equation 5-8 (values for parameters appear in Section D.6, Appendix D)

$$D_{HHspecific\_lights}(i,j) = D_{HHgroup\_lights}(i,j) \times k_{occ\_lights}(i,j) \times k_{lifestyle\_lights}(i,j) \qquad \textbf{[5-8]}$$

where:

$D_{HHspecific\_lights}$ is the half-hourly demand assigned to a specific consumer

$D_{HHgroup\_lights}$ is the group-averaged half-hourly demand (Equation 4-26)

k_{occ_lights} is a scaling factor depending on number of occupants

$k_{lifestyle\_lights}$ is scaling factor depending on ACORN classification (or k_{income_lights} is used instead if income data are available)

i is the test day number, j is the half-hourly reference number

5.8 Miscellaneous demand – half-hourly, specific

5.8.1 Ownership of miscellaneous appliances

It is assumed that all domestic consumers will have some element of demand that is not covered by the previous categories of demand. A need for miscellaneous demand is assigned, to varying extents, at all domestic connection points on the LV network.

5.8.2 Effects of occupancy, income and lifestyle factor on miscellaneous demand

Miscellaneous demand is likely to arise from the use of multi-media appliances (televisions, DVDs, etc.), computers and peripherals, portable heaters and a variety of small domestic appliances. Like lighting demand, most of these items are associated directly with occupant activity, unlike demands that arise from cooling or wet appliances. For the purposes of this model, the same values that change the daily profiles and the overall scale of demand that have been described for lighting are also used for miscellaneous demand. Thus the miscellaneous category of demand is adjusted for occupancy and either income or lifestyle classification. These scaling factors are applied to the group averaged miscellaneous demand from the first layer of the model.

5.8.3 Description of miscellaneous demand for layer 2

Miscellaneous demand is calculated using equation 5-9 (values for parameters appear in Section D.6, Appendix D) using the same scaling factors as for lighting demand:

$$D_{HHspecific\_misc}(i,j) = D_{HHgroup\_misc}(i,j) \times k_{occ\_lights}(i,j) \times k_{lifestyle\_lights}(i,j) \qquad [5\text{-}9]$$

where:

$D_{HHspecific\_misc}$ is the half-hourly demand assigned to a specific consumer

$D_{HHgroup\_misc}$ is the group-averaged half-hourly demand (Equation 4-28)

k_{occ_lights} is a scaling factor depending on number of occupants

$k_{lifestyle\_lights}$ is scaling factor depending on ACORN classification (or k_{income_lights} is used instead if income data are available)

i is the test day number, j is the half-hourly reference number

5.9 Total demand – half-hourly, specific

The demands described so far are the active components for each appliance or end-use. The reactive components can be calculated using the power factors (Equations 3-13 and 3-14) for which values are provided in Appendix D, section D.8. Most of the load arises from resistive appliances with a power factor of 1 although this will fall to around 0.7 for purely cooling devices and around 0.9 for the spin cycle of washing appliances [Newborough & Augood, 1999]. The total reactive demand for each half-hour is the sum of the calculated reactive components for each of the end-uses or appliances (which in most cases will be zero). The total overall demand (which is the vector sum of the active and reactive loads) and the power factor for each half-hour are calculated from equations 3-17 and 3-18. The total demand represents the assignment to an individual domestic consumer at a connection node on the LV network (Figure 5-8).

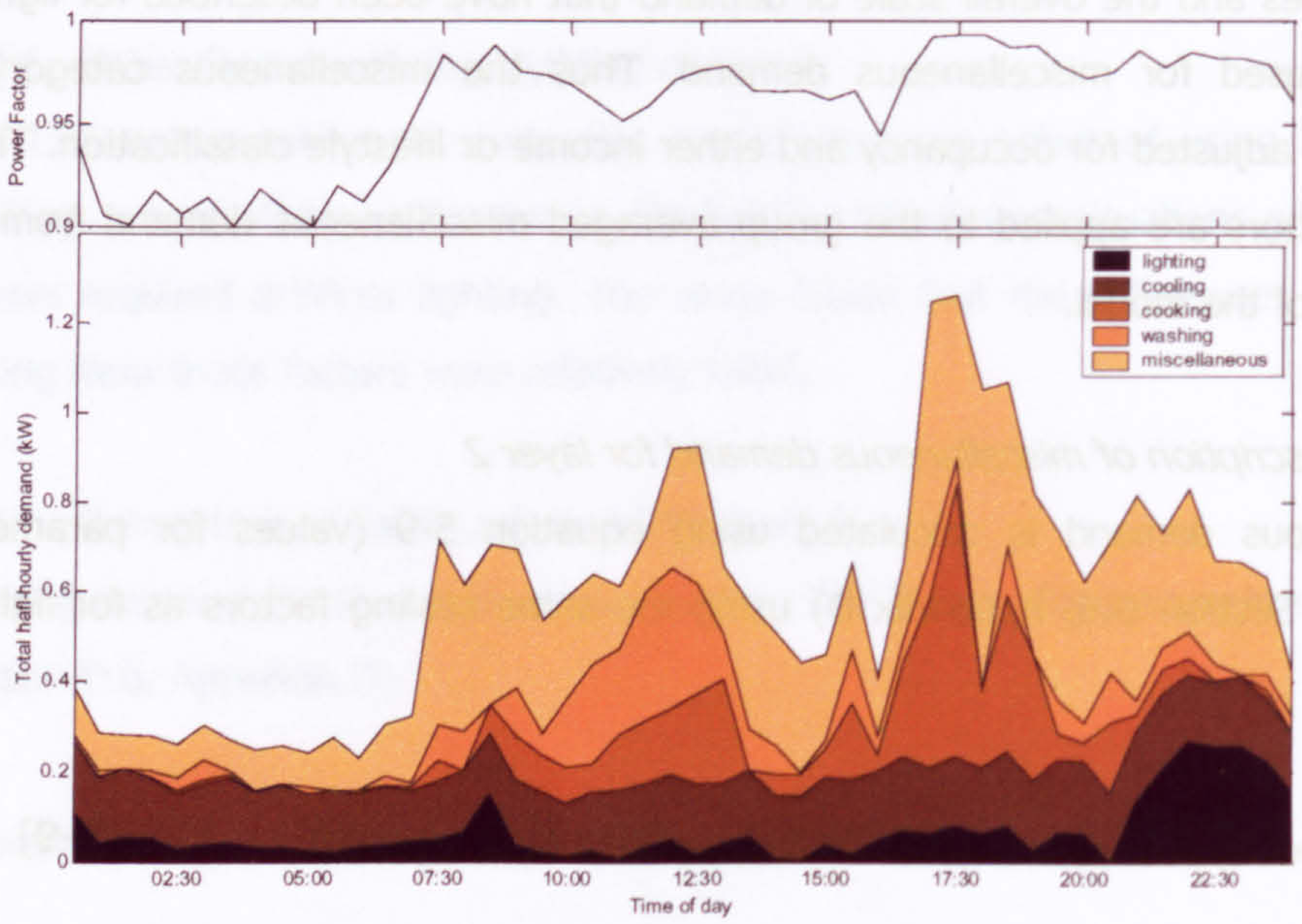


Figure 5-8: Example of total assigned half-hourly demand showing end-use/appliance contributions and the estimated power factor (half-hourly for detached house, 4 person, lifestyle rating 'B' with non-electric water and space heating, 7th June, 2004).

Homes of the same description (in terms of appliance ownership, occupancy, income, lifestyle factor, etc,) will be assigned the same half-hourly pattern in layer 2 of the model. The output from layer 2 is a modified version of the group averaged pattern, not necessarily the representation of a half-hourly demand for an individual consumer. To derive this, it is necessary to estimate the 1-minute demand patterns and to recalculate the half-hourly demand.

Using the earlier example (shown in Figure 5-8), whilst the contribution from washing appliances is a significant part of the total demand around mid-day, this consumer has also been assigned a small demand for washing appliances throughout the day. This is unrealistic and occurs because the assigned demand has been scaled from the group-averaged demand patterns, where, within a group of homes, a small number of consumers may be using washing appliances at any time of the day. Even when scaled by the diversity factors described, some small residual demand is likely to exist when in practice there is none. The model is therefore required to provide a method that creates significant demand in some homes and none in others.

When the third layer of the model is used to synthesize 1-minute demands, the assigned half-hourly demand is used as a probability. The chance of a washing event occurring is remote when the assigned half-hourly demand is very low. When the 1-minute demand from layer 3 of the model is averaged again at the half-hourly level, the demands for some of the end-uses will contribute a greater demand for a short time but no demand at other times of the day.

For one particular run of the model, using the washing machine demand assigned in the earlier example (Figure 5-8), two washing events are triggered, one in the morning and evening (Figure 5-9). A significant cooking event occurs at mid-day (use of an oven) with two minor events later in the day (kettle and microwave). The demands for lighting, cooling and miscellaneous appliances demonstrate slightly more variability in level when calculated from the 1-minute demands of layer 3, compared to the assigned demands of layer 2. For these kinds of end-uses, the appliances generally create a more continuous, lower level demand (at the half-hourly level) and hence the diversity between homes has mostly been accounted for by using occupant factors to scale the group averaged patterns. The overall result is a much spikier total demand pattern, which is likely to be more realistic and includes more diversity, compared to the assigned half-hourly demand from layer 2 of the model.

This ensures diversity in demand either for the same house on different days as well as diversity between houses with the same description (Figure 5-10). Consequently the assigned half-hourly demand from this layer of the model has limited uses. It could provide a crude model of half-hourly demand for a particular consumer for the purposes of estimating daily, monthly or annual energy demands and the contributions from specific appliances, both in terms of the active and reactive loads. The main purpose of the specific half-hourly demand estimate, however, is to provide the input for the generation of 1-minute demands in layer 3, which is described in more detail in the next chapter.

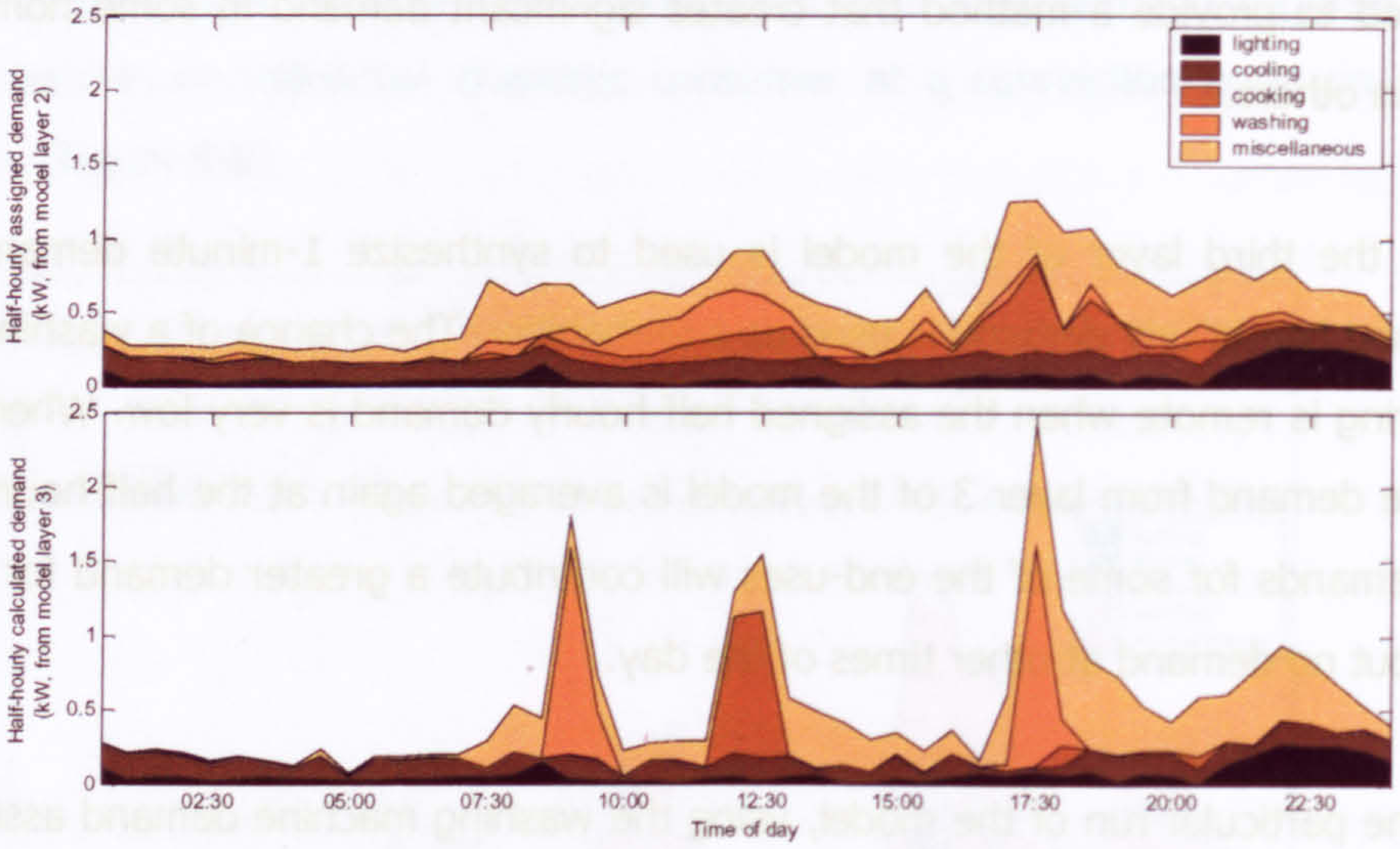


Figure 5-9: Comparison of the assigned half-hourly demand from layer 2 of the model with that calculated from the 1-minute demands of layer 3 (detached house, 4 person, lifestyle rating 'B' with non-electric water and space heating, 7th June, 2004)

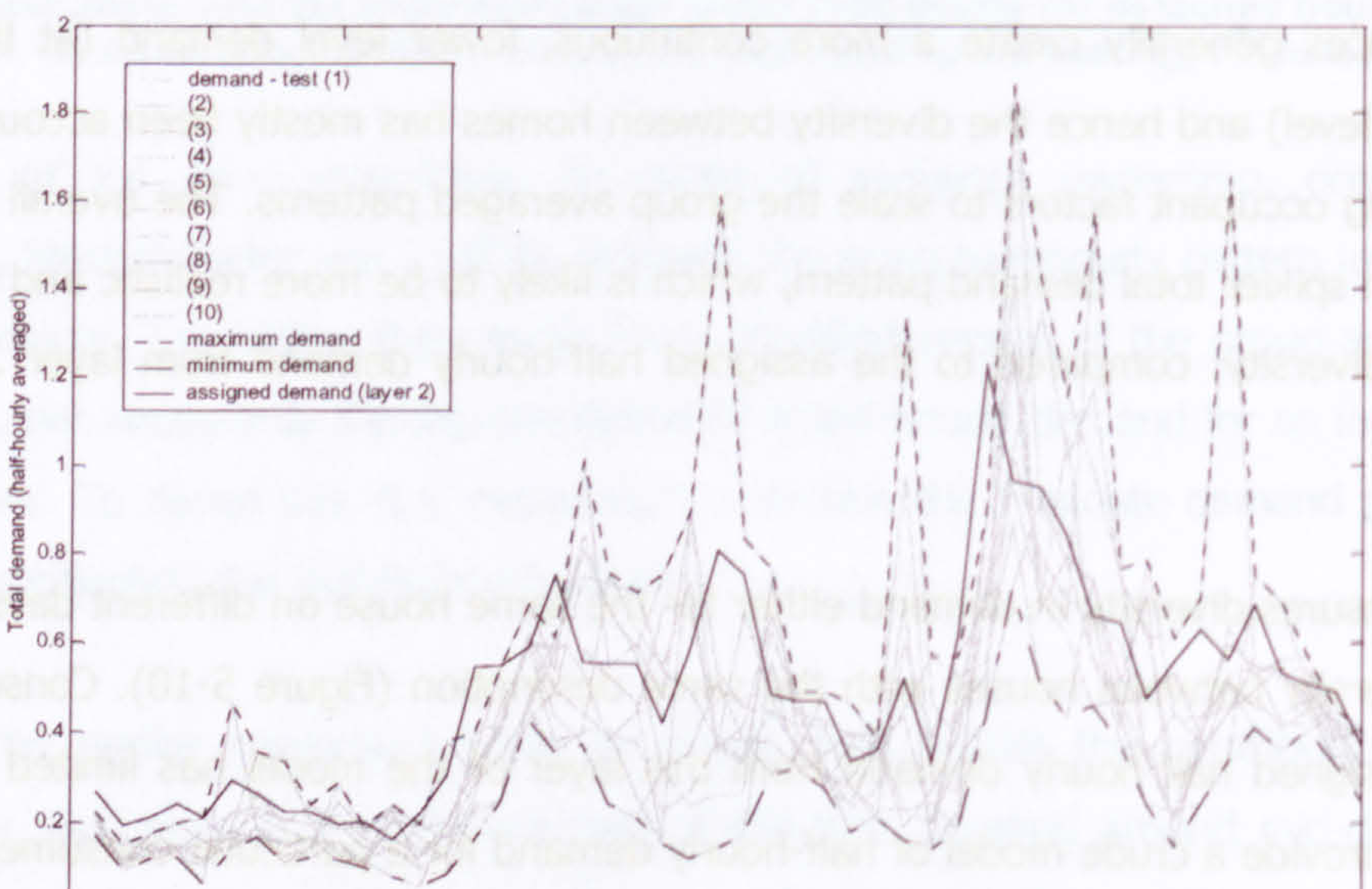


Figure 5-10: Comparison of the total demand for ten runs of the 1-minute demand calculations of the model (layer 3), averaged half-hourly, together with the assigned demand (layer 2) (1960s semi-detached house, 4 occupants, unrestricted tariff, ACORN category C, with electric oven, microwave, kettle, fridge, freezer and washer-dryer, 8th June, 2004)

5.10 Summary: Chapter 5

The purpose of layer 2 of the domestic load model is to introduce elements of diversity, making the group-averaged demands from layer 1 more specific to individual connection points on the LV network. Building and occupant related factors have been examined, of which appliance ownership and levels of occupancy (based on floor area) are the most significant. Socio-economic factors, such as lifestyle rating and income, are used for scaling and shaping daily profiles and for varying levels of ownership.

The output from this layer provides half-hourly demands based on end-use and as such the relative contributions allow estimates of the power factor. However, homes with the same specification are assigned identical demands and further diversity, introduced in the 1-minute averaged demands of layer 3 of the model, is required to make the network load descriptions more realistic.

Chapter

6

Domestic Model: Layer 3

(Specific, one-minute demand)

Every minute dies a man,
And one and a sixteenth is born
Charles Babbage

In any given minute someone in the UK will be switching on a light, boiling a kettle, washing clothes, watching television or cooking food. Whilst in broad terms our underlying behaviour is fairly predictable (most people sleep at night, eat a meal in the evening, etc.) often the reason behind the precise timing of an action is obscure, perhaps even to ourselves. It is certainly impossible to model without using some element of chance. Whilst, in an individual house, knowing a little of the occupants and their habits, it may be feasible to deduce what will happen in a given half-hour. To describe the minute by minute electricity demand requires the use of probability, the basis for which will be described in this chapter.

This third and final layer of the domestic model provides an output that is the 1-minute averaged total demand (both active and reactive components) that is assigned to a particular domestic connection point. This chapter begins by outlining the concepts of this last piece of the jigsaw. The sections that follow look at the assumed duty cycles for each end-use/appliance and explain how a demand event is triggered.

6.1 General concepts of the domestic model, final layer

6.1.1 Representing diversity

Demand arising from consumers can be considered an amalgamation of four components, which are partially inter-dependent:

- *existence of the demand arising from ownership*

  e.g. only around 10% of UK homes use electricity for space heating [DEFRA,2001]
- *scale of the demand*

  e.g. houses with 8 main rooms consume 80% more electricity for lighting compared to those with only 5 [Electricity Association, 1998(b)]
- *timing, frequency and duration.*

  e.g. homes occupied by 4 adults use a washing machine 7 times per week on average compared to one adult with 2.6 cycles per week [Mansouri et al, 1996]
- *efficiency of appliances*

  e.g. homes with low energy light bulbs use around 8% less electricity for lighting per annum than those without [Electricity Association, 1998(b)]

In the first layer of the model, all these elements of diversity are combined together, since the demand modelled is the average for a large group of domestic consumers. The rest of the model has to unravel the mixture of diversity factors, which vary in nature and degree from one end-use to another. In the second layer, the assigned demand is made more specific by including diversity arising from ownership and variations in the scale of the demand due to occupancy, income or lifestyle classification. To some extent, timing is also included by assigning different tariffs and hence varying patterns of demand. These elements of diversity must be matched from one layer of the model to another. In layer 3, the model compares the power required by a standard appliance to the power assigned to a given connection point for each half-hour. This ratio is used as a probability. If the demand assigned is high, the corresponding probability will be high and an appliance event is likely to be triggered. Thus if several appliances are owned or if the frequency of use is high, scaling up the assigned demand in layer 2 leads to more appliance events being triggered in layer 3.

The remaining diversity factors relate more to the appliances themselves – efficiency and designed performance. For some end-uses, there is further diversity introduced in terms of assigning a power rating for a particular appliance within a range. Thus for the same half-hourly demand a smaller appliance will be used more frequently or for a longer duration. This introduces variation in terms of appliance rating, design and efficiency. When diversity is likely to arise from varied use patterns of several appliances of the same type (such as light bulbs), the model allows more than one event to occur at the same time, with decreasing probability as more of the assigned demand is allocated to each triggered event. In some cases variations in appliance duty cycles are modelled. For example, random selection from ten different hob settings and from four hob elements gives greater diversity in the detailed patterns for cooking demand. In this way, the final layer of the model attempts to capture more of the factors of diversity that are present in the original group averaged data. A complete description of the appliance duty cycles used for the model are provided in Appendix E.

6.1.2 Example illustrating the basic concepts used in layer 3

The following example describes a typical application of the final part of the domestic model to illustrate the underlying concept. A household with four occupants is assigned a kettle power demand of 0.047 kW between 17:30 to 18:00 on the 1st January, 2005 from layer 2 of the model. The house is assumed to have a kettle rated at 2.4 kW (selected randomly between 2-3 kW, a typical range for current kettle appliances) which boils for 4 minutes (also selected randomly between 2-5 minutes, a typical range for boiling kettles, which in reality depends on the amount of water boiled and the kettle rating), giving an averaged half-hourly demand requirement of 0.32 kW (2.4 multiplied by 4/30). The ratio of the assigned demand and the required kettle demand is 0.15 (0.047 divided by 0.32), giving a 15% probability that this event will occur. A linearly generated random number (between 0-1) is compared with this probability and if less than or equal to 0.15, the event is triggered. In this example, an event is activated and the start time is randomly selected to occur at any time between 17:30 and 18:00[1]. For this example,

[1] The start time may occur at any minute during the half-hour. The random distribution of start times is assumed to be linear and there is no account for distortions (such as a tendency to carry out activities on the hour) in this distribution. Coincident appliance events, leading to daily peaks, may occur and are determined entirely by the random triggering of events. This process is of course guided by the measured patterns from the group averaged LRG data.

the kettle is assumed to boil from 17:52 until 17:56 at the rated power level (Figure 6-1). This process is described in the general equations of 3-10 to 3-12 and shown with application to this example in equations 6-1 to 6-6.

Pr (event occurring) = $D_{HHspecific\_n}(i,j)$ / $D_{HH\_appliance\_n}$

where $D_{HHspecific\_n(i,j)}$ is the assigned half-hourly demand to a specific consumer, in this case, $D_{HHspecific\_kettle}(1,36) = 0.047$ **[6-1]**

$D_{HHappliance\_n}$ is the half-hourly averaged demand of the appliance, in this case a load of 2.4 kW lasting 4 minutes in the half-hour
in this case, $D_{HH\_kettle} = 2.4 * 4/30 = 0.32$ **[6-2]**

Hence, Pr = 0.047/0.32 = 0.15 or 15% **[6-3]**

R is a randomly generated number, in this case R = 0.10
if R ≤ Pr, event is triggered
in this case, event is triggered with a randomly selected start time of 17:52 and lasts for 4 minutes. The remainder of the kettle demand during the half-hour is set to zero. Thus:
$D_{min\_kettle}(1,1051:1071) = 0$ **[6-4]**
$D_{min\_kettle}(1,1072:1076) = 2.4$ **[6-5]**
$D_{min\_kettle}(1,1076:1080) = 0$ **[6-6]**

For each end-use, the various elements of the demand description (start time, duration, power rating, etc.) are adjusted to fit the relevant factors that affect diversity. The sections that follow provide more detail.

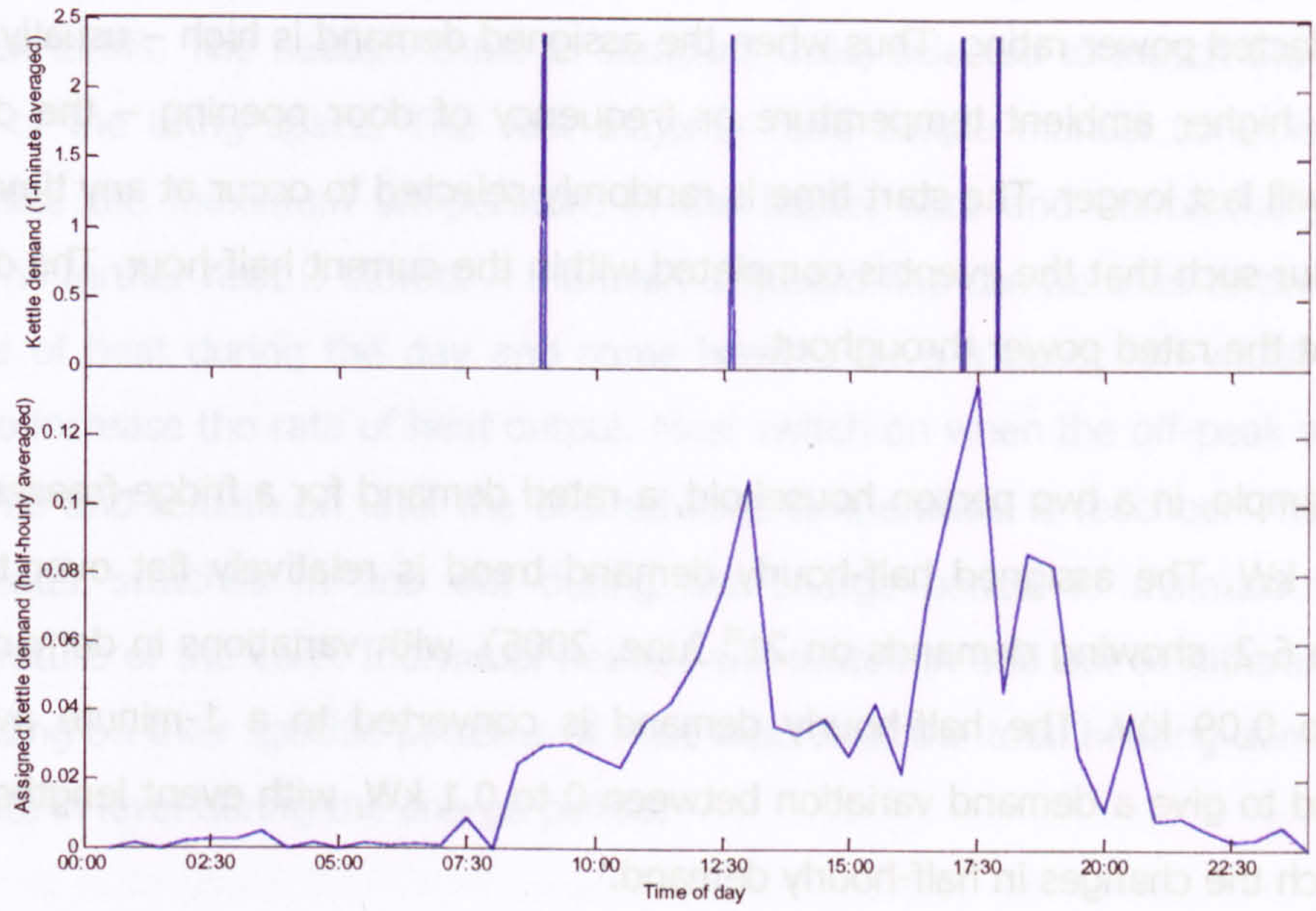


Figure 6-1: 1-minute (top) and half-hourly (bottom) averaged kettle demands calculated for a 4-person household on the 1st January, 2005.

6.2 Cooling demand – 1-minute, specific

For this and all other end-uses, a calculation of the 1-minute demands is only made when ownership of an end-use or appliance has been assigned in layer 2. In the case of refrigerators and fridge-freezers, the power rating of the appliance is scaled depending on the number of occupants in the household (to match the assumptions about scaling the half-hourly demand, made in layer 2). The mean of appliance demand ratings is assumed to be 0.060 kW and 0.120 kW for a refrigerator and fridge-freezer respectively (based on a limited sample of current retailed models). These ratings are scaled up or down in relation to the occupancy, assuming 2.4 people per household is the national average. Freezer ratings are assumed to be independent of occupancy (as discussed in Section 5.2.2) and are selected randomly using a normal distribution with a mean of 0.093 kW and standard deviation of 0.020 kW.

The ownership of cooling appliances assigned previously allows for multiple fridge-freezers or freezers per household and each assigned appliance is treated completely separately. For all cooling appliances, it is assumed that one event will occur every half-hour, the duration of which is calculated from the assigned half-hourly demand and selected power rating. Thus when the assigned demand is high – usually arising from a higher ambient temperature or frequency of door opening – the demand event will last longer. The start time is randomly selected to occur at any time in the half-hour such that the event is completed within the current half-hour. The demand is set at the rated power throughout.

For example, in a two person household, a rated demand for a fridge-freezer would be 0.1 kW. The assigned half-hourly demand trend is relatively flat over the day (Figure 6-2, showing demands on 21st June, 2005), with variations in demand from 0.05 to 0.09 kW. The half-hourly demand is converted to a 1-minute averaged demand to give a demand variation between 0 to 0.1 kW, with event lengths varied to match the changes in half-hourly demand.

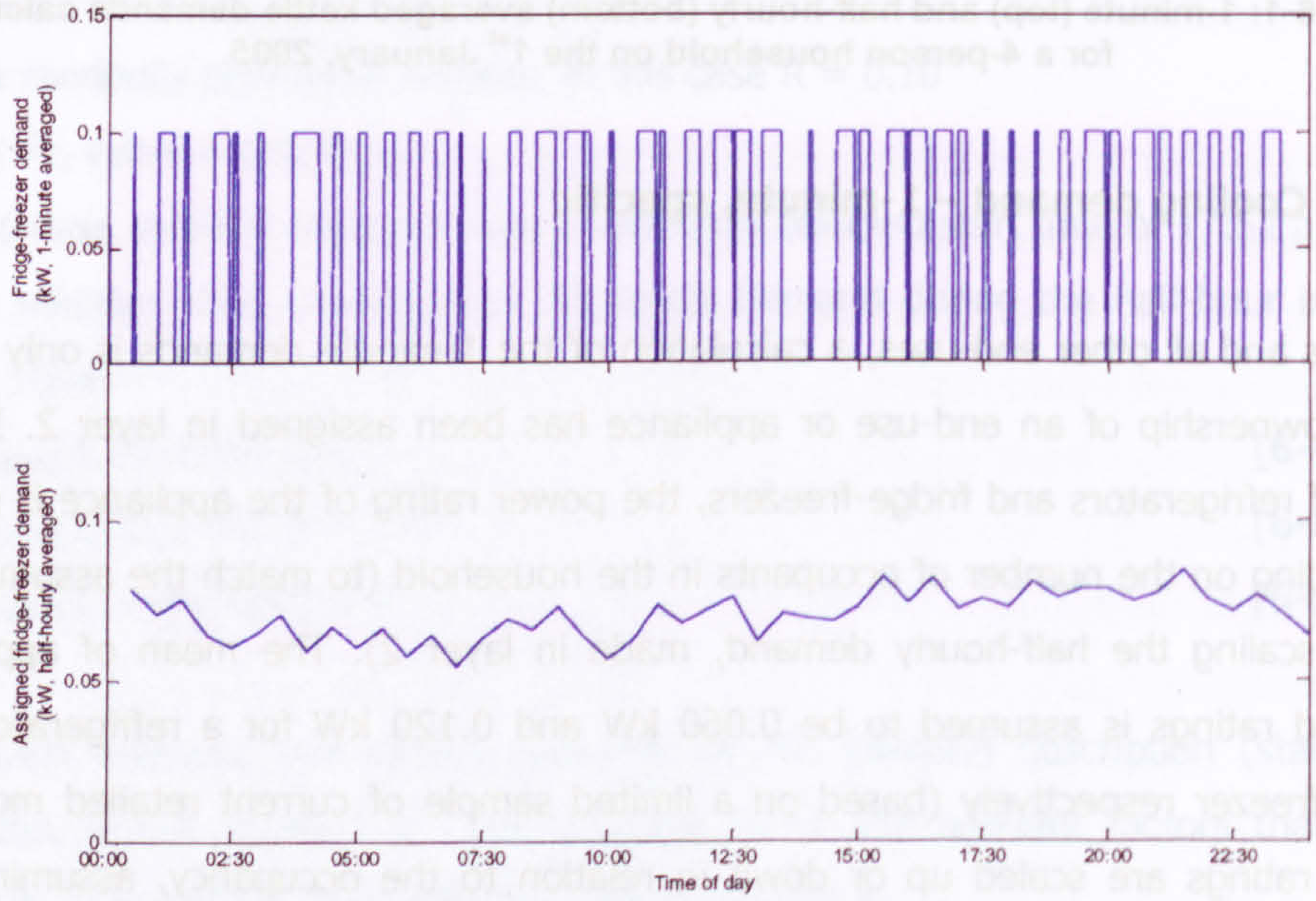


Figure 6-2: 1-minute (top) and half-hourly (bottom) averaged fridge-freezer demands for a 2-person household on the 21st June, 2005

6.3 Space-heating demand – 1-minute, specific

Storage heaters were introduced in the UK during the 1970s to make better use of the electricity generated overnight in the new nuclear power stations and to reduce the level of the daytime peak [Wright, 1997]. They are designed to operate for 7-8 hours, the charge period being automatically determined by the local operation of off-peak tariffs. The heaters come in standard sizes, selected to match the heating needs of the living space. The vast majority have simple manual controls, which determine the maximum temperature in the heater core and hence the point at which no further heat is stored. A manually adjusted flap can be used to control the release of heat during the day and some heaters have a boost fan which can be used to increase the rate of heat output. Most switch on when the off-peak supply is triggered and remain on until the desired core temperature is reached. Thereafter, the heater switches in and out during the charge period to maintain the set temperature of the core. Individual heaters will switch in and out at different times depending on their specific patterns of heat loss. Thus the total heating demand will fluctuate in level during the charge period.

This behaviour is very much simplified for the purposes of the model but is considered adequate to meet the research objectives. The model assumes that the charge period runs from 23:30 to 08:30 which is longer than in practice. The original LRG half-hourly data appear to include consumers supplied with different off-peak timing and the period selected from the model includes the range of all tariffs used. The maximum heating demand (which in reality would be the sum of demand from each heater, which in turn depends on the power rating and manual setting) is taken as the maximum assigned half-hourly demand that occurs before 08:30 on a given day.

For example, a home with a floor area of 86m^2 is assigned a maximum half-hourly average demand for the 21st December, 2005 of 8.29 kW (Figure 6-3). This value is assumed to be the rated demand for that day. The half-hourly peak is reached between 01:30 and 02:00. Until and during the half-hour when the maximum demand occurs, it is assumed that the heater remains on throughout the entire 30 minutes at the same level (the demand assigned in layer 2). Thereafter, the duration of the heating event is calculated to occur at the rated heating demand for the day, in this case 8.29 kW, for a period that gives the same demand as that assigned when averaged over each half-hour. The event begins at any minute such that the entire event occurs within the half-hour in question. This allows the demand to cycle on and off during the charge period. During the on-peak hours, the demand is very low and is set at a constant level to match the assigned half-hourly demand. In the final half-hour of the day, the heater is assumed to be on, at the level of the assigned demand.

In practice, the level of heating demand will fluctuate more than the model suggests but is likely to run at the maximum demand from the start of the off-peak charge period (when all the heaters in a house are on full demand). The gradual increase in demand predicted by the model arises from the original LRG data. The model would be more accurate if an estimate were made of the number of heaters in the house and each treated as an individual demand with random elements to vary the event duration and timing. The charge period could be limited to just 7 or 8 hours, using a gate in the model to limit the demand assigned. However, since only 1% of consumers in England use storage heaters [ODPM, 2001] and since such heating is unlikely to influence the network loading at times when embedded solar generation is available (unless some storage capacity were provided during daylight hours), these issues are not considered in this version of the model.

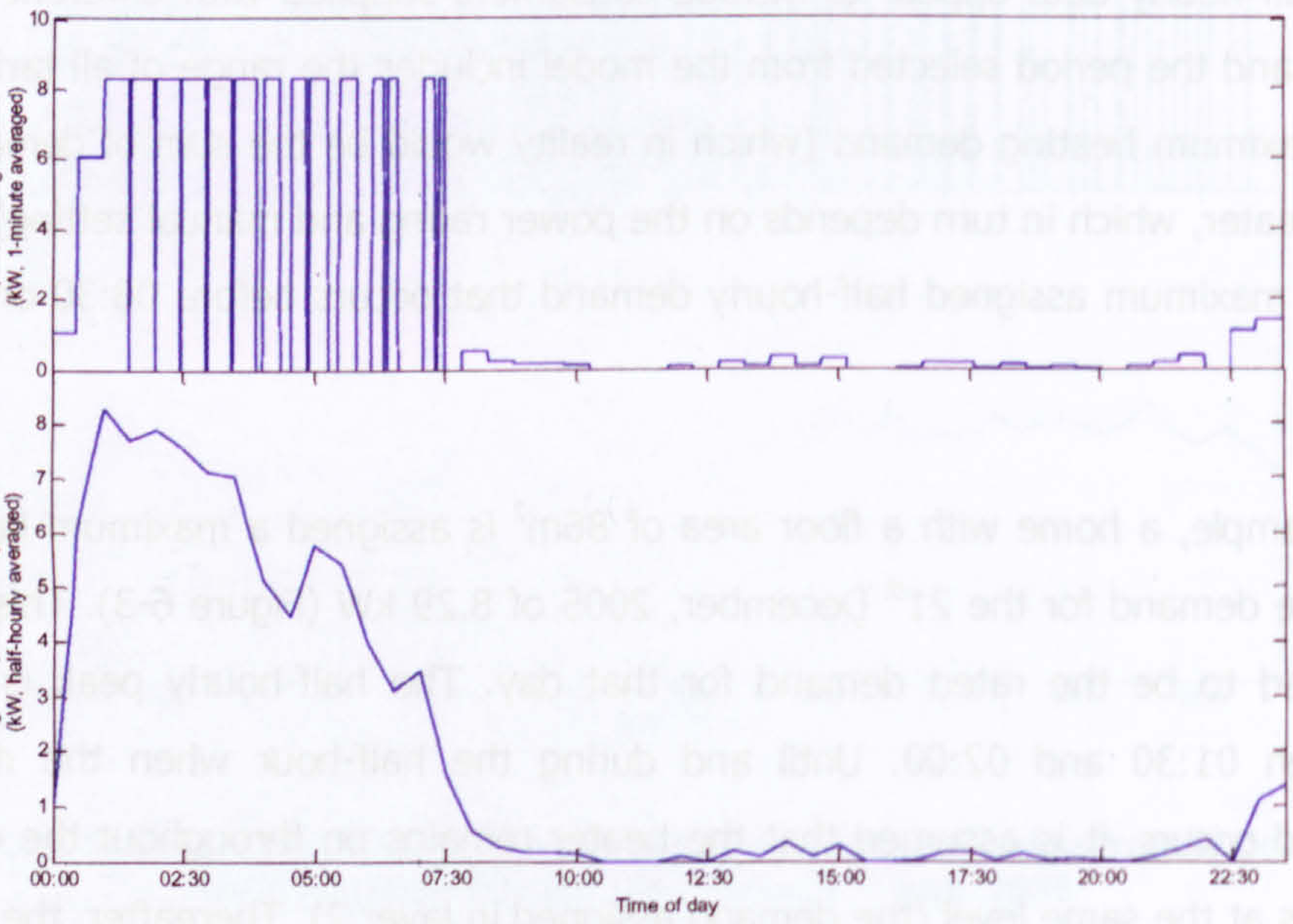


Figure 6-3: 1-minute (top) and half-hourly (bottom) averaged space-heating demands for a domestic consumer (floor area 86m^2, off-peak tariff, 21st December, 2005)

6.4 Water heating demand – 1-minute, specific

Immersion heaters are normally available in three standard sizes – 1, 2 or 3 kW ratings. The size of the immersion heater is generally sized to suit the likely demand – based on floor area or number of bedrooms (indicating number of occupants). More sophisticated systems use a 3kW primary element for bulk heating together with a 1 or 2kW secondary element placed at the top of the hot water tank, which supplies additional heating as water is drawn. Water heating will switch on either as a result of an automatic timer, off-peak trigger or human intervention. Water is usually heated in a storage tank until a preset temperature is reached from which point, the immersion heater cuts in and out to maintain the set temperature during the charge period. The heater is switched off manually or by automatic controls.

Diversity at the 1-minute level is likely to arise because of the frequency and extent of hot water usage (higher occupancy being linked to a greater demand), the control strategy (typically timed heating periods with manual over-ride), timing (the timer settings, if controlled automatically) and the heat loss from the water cylinder which affects the duration of the heating period. Again, the model simplifies these issues considerably.

For each consumer, the rating of the immersion element is selected, on the basis of floor area, from the standard power ratings (this selection is not currently linked to occupancy, income or lifestyle factor). It is assumed that a typical water heating event is likely to last around 15 minutes. The half-hourly averaged demand for a 15 minute event is used in relation to the assigned half-hourly demand to assess the probability of an event occurring. For example, a 2kW immersion heater operating for 15 minutes in a half-hourly period creates an averaged demand of 1kW. The assigned half-hourly demand for the consumer (a 2-person household) is 0.009 kW (unrestricted tariff, 08:00-08:30 on 21st December, 2005). The probability that a heating event will occur in this half-hour is taken to be 0.9% and thus, an event is unlikely to occur. If a heating event is triggered, the duration of the event is calculated from the power rating and assigned half-hourly demand, with a minimum time span of 15 minutes. The start time of the event is selected at random such that the event is completed within the given half-hour.

This strategy tends to give several water heating events during the day of relatively short duration which is not entirely realistic (for example with an unrestricted tariff demand, Figure 6-4, and off-peak tariff demand, Figure 6-5). The LRG group averaged data show a very low level of demand for water heating which may be caused by the averaging of a mixture of both all year round and summer only users or by including consumers who own immersion heaters but generally use other means to heat water.

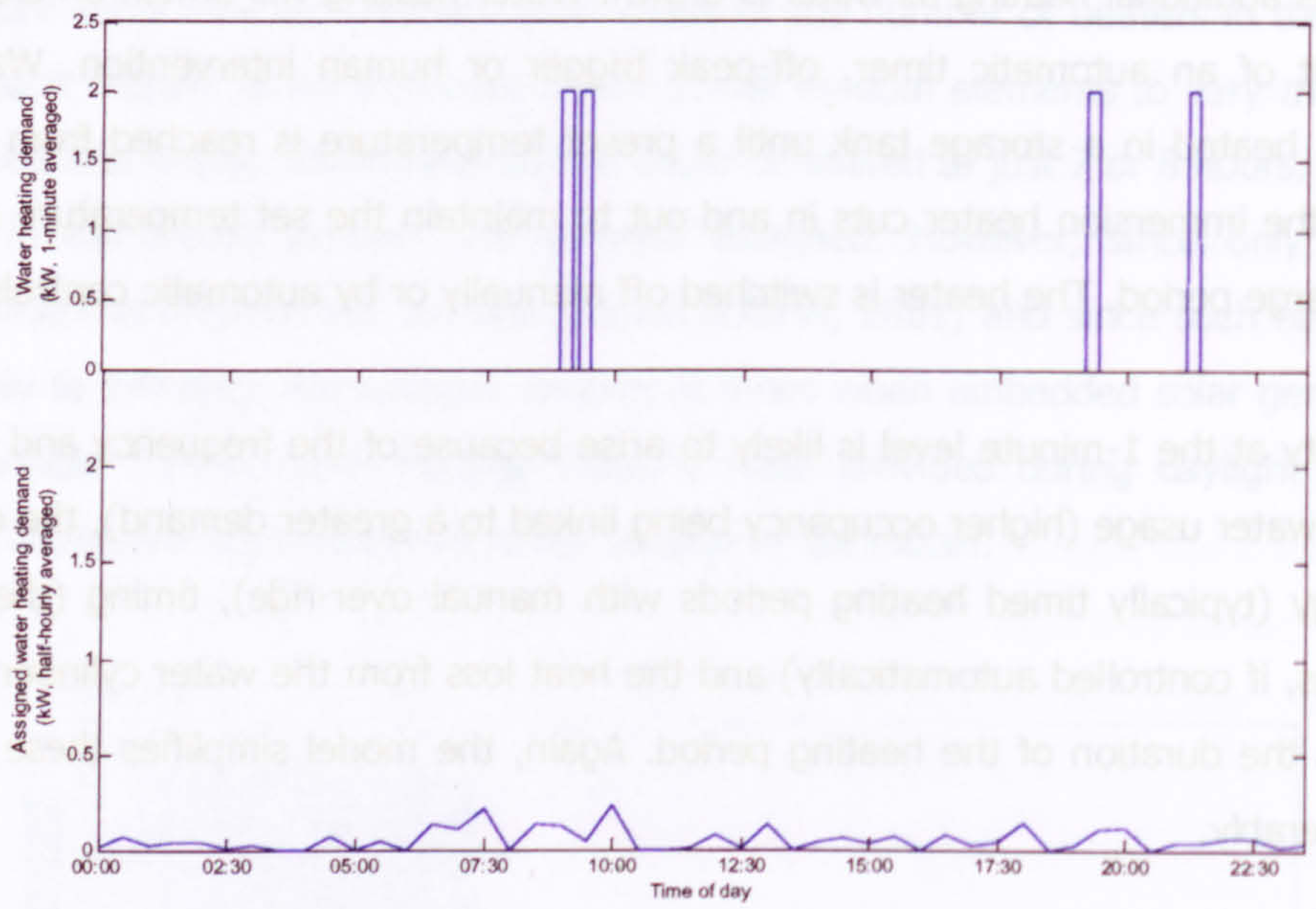


Figure 6-4: 1-minute (top) and half-hourly (bottom) averaged water-heating demands for a domestic consumer (2 occupants, unrestricted tariff, 21st December, 2005)

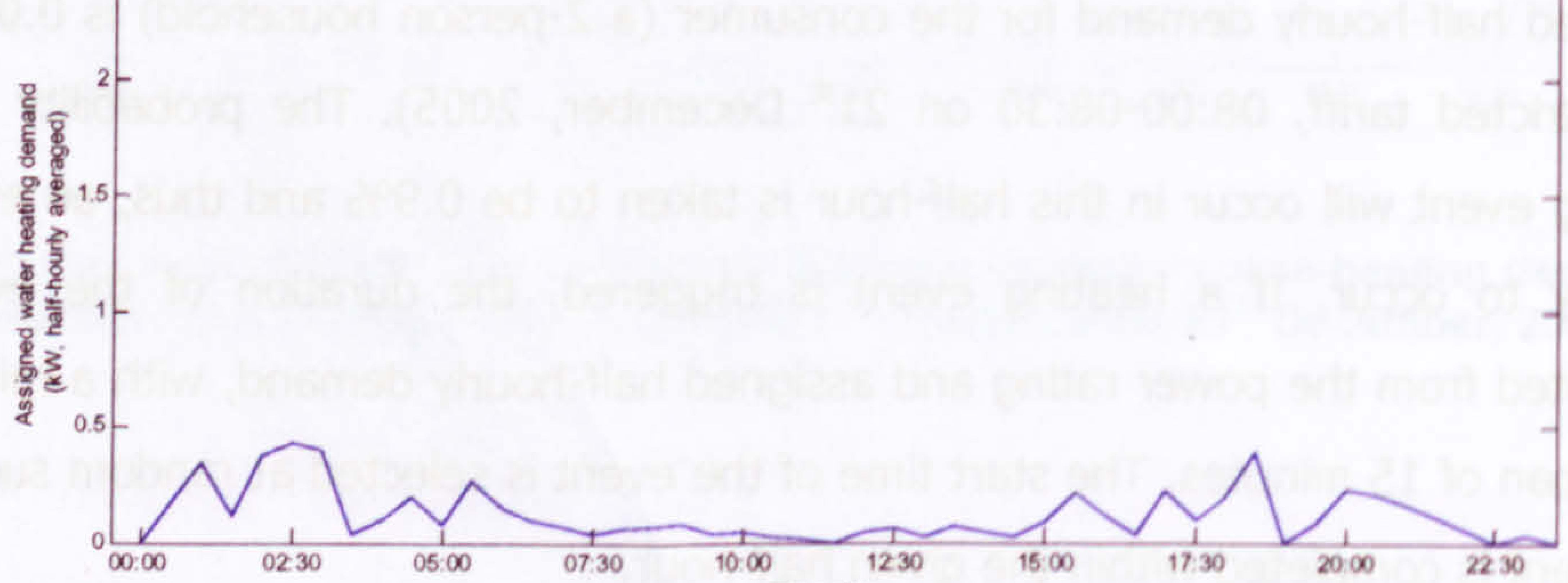


Figure 6-5: 1-minute (top) and half-hourly (bottom) averaged water-heating demands for a domestic consumer (2 occupants, off-peak tariff, 21st December, 2005)

Alternative strategies for the model include reducing the rated power, reducing the typical event length or summing assigned demand across several half-hourly periods to trigger events. There are problems with each of these but, as for space heating, since there are relatively few consumers who use electric water heating, especially in urban areas where a gas supply is more likely to be available, the model is considered to be adequate for the intended purpose.

Whilst there are few published UK studies of water heating demands at the 1-minute level, some data for domestic water heating were obtained from a study of demand in New Zealand homes [McQueen et al, 2003]. The demand characteristics from 87 daily records suggest that immersion heaters (which are restricted to a maximum 2.25 kW maximum rating in New Zealand) operate for programmed periods, together with intermittent bursts of demand to maintain a constant temperature in the storage tank (Figure 6-6).

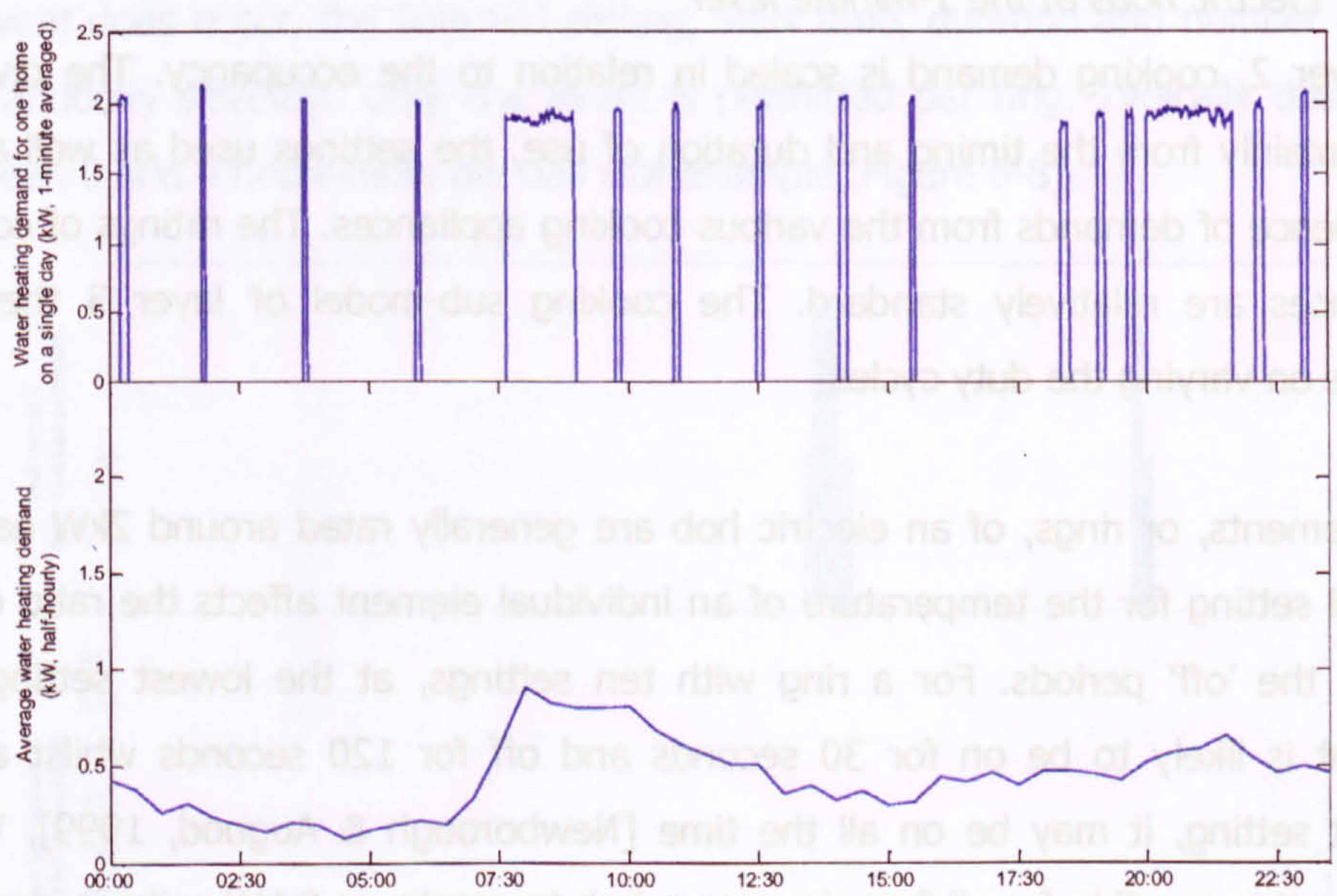


Figure 6-6: Measured 1-minute water heating demand for a specific day and house (top) and the group averaged half-hourly demands (bottom) for electric water heating (taken from a sample of 87 daily demand records, homes in New Zealand [McQueen et al, 2003])

When the group averaged half-hourly demands are used as an input to layer 3 of the model, the resulting 1-minute modelled water heating demands are more intermittent (Figure 6-7) than the 1-minute measured data (Figure 6-6, top). It is interesting to note that the sample averaged demand for the New Zealand study is at a higher level than for the LRG data (comparing the lower graphs of Figures 6-5 and 6-6).

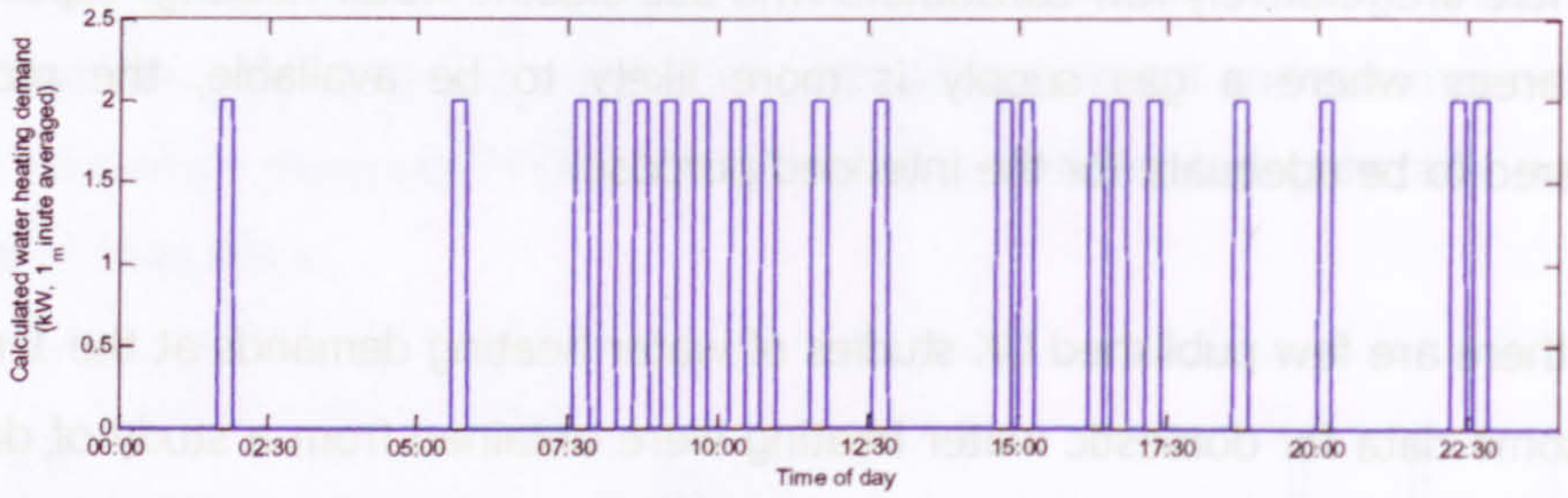


Figure 6-7: 1-minute averaged demand calculated by one run of the model (based on the group averaged half-hourly demands shown in Figure 6-6)

6.5 Cooking demand – 1-minute, specific

6.5.1 Electric hobs at the 1-minute level

For layer 2, cooking demand is scaled in relation to the occupancy. The diversity arises mainly from the timing and duration of use, the settings used as well as the coincidence of demands from the various cooking appliances. The ratings of cooking appliances are relatively standard. The cooking sub-model of layer 3 therefore focuses on varying the duty cycles.

The elements, or rings, of an electric hob are generally rated around 2kW each. A manual setting for the temperature of an individual element affects the ratio of the 'on' to the 'off' periods. For a ring with ten settings, at the lowest setting, the element is likely to be on for 30 seconds and off for 120 seconds whilst at the highest setting, it may be on all the time [Newborough & Augood, 1999]. Whilst unlikely, it is possible for all four rings on a hob to create an 8 kW spike in demand. Consequently, it is important for the model to capture this kind of behaviour with reasonable accuracy. The situation is simplified with a random selection of settings from 1 to 10. Each setting is linked to a 5-minute duty cycle, using a rated power demand of 2 kW. A setting of 1 causes a demand of 2kW for 30 seconds and then no demand until the end of the 5 minute cycle. A setting of 5 causes a 2 kW demand for 50% of the cycle whilst the maximum setting causes a continuous 2kW demand.

Mansouri et al's study [Mansouri et al, 1996] provides an indication of which rings are likely to be in use on a typical day. For example, 97.6% of the sample claimed to use ring 1 whilst around half rarely use rings 3 or 4 at all. This provides a probability of use. If a ring event is triggered the duration is selected randomly between 5-135 minutes, using Mansouri et al's study for the distribution. For example, for ring 1, around a fifth reported using it for less than 15 minutes per day and around 40% for between 15-30 minutes (the values used in the model appear in Appendix E). The distribution of duration varies from one ring to another.

To trigger an event, it is assumed that a typical duration is likely to be for about 20 minutes at a mid-setting, i.e. a half-hourly averaged demand of about 1.5 kW (based on a limited study of hob use in the author's home for 5 days). This is compared with the assigned half-hourly demand to provide a probability of an event occurring. The probability is adjusted to improve the match between the model output and the MTP's trend data for the total number of hob use events per year [DEFRA, 2001][2]. If an event does occur, the selected setting, start time, duration and number of rings are randomly selected. Only one event is permitted per ring. Typically this causes between 0 and 4 hob events per day (for example, Figure 6-8).

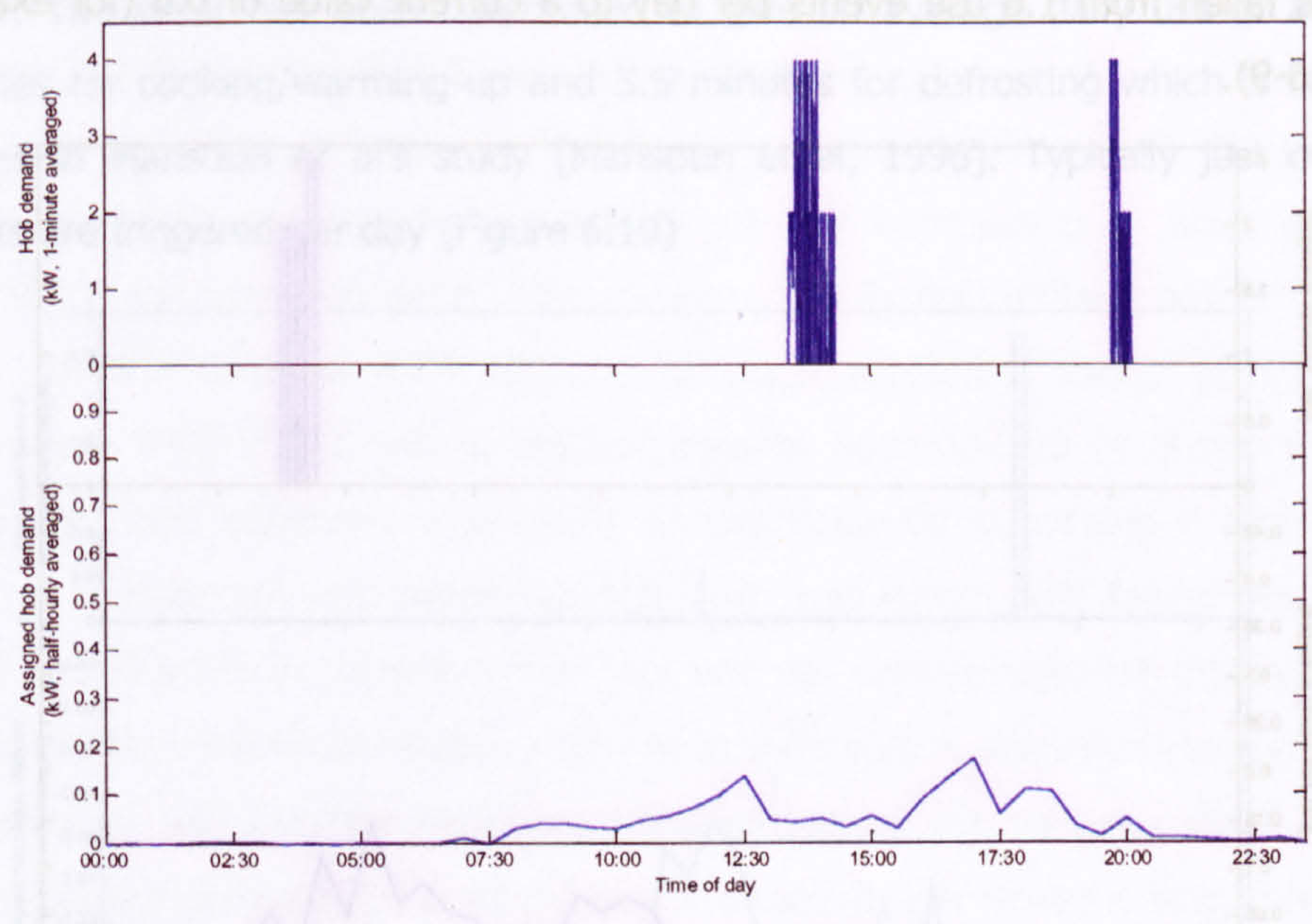


Figure 6-8: 1-minute (top) and half-hourly (bottom) averaged hob demands for a domestic consumer (2 occupants, 21st December, 2005)

[2] The MTP data suggest that the current figure is 1.01 hob events per day, having fallen from around 1.5 in the 1970s

6.5.2 *Oven demand at the 1-minute level*

Oven demand signatures are characterised by a pre-heat period of between 5-20 minutes with a cooking cycle during which the element switches on and off via a thermostatic control to maintain the correct oven temperature. The cycling tends to be in minutes rather than seconds [Newborough & Augood, 1999].

To model the demand, a pre-heat rating of 2.5 kW is applied for a duration of 5-20 minutes, depending on the random selection from five different temperature settings. Following this, there is a cooking period at a peak demand of 2.0 kW with duration randomly selected using a normal distribution (mean value 35 minutes, standard deviation of 10 minutes, based on Mansouri et al's study). The heating element is assumed to cycle on and off within a 10 minute period, such that a minimum setting heats for 1 minute and a maximum setting for 5 minutes in each period.

The event is triggered based on a comparison of the assigned half-hourly oven demand and a typical oven event, (half-hourly average of 1.5 kW). This probability is adjusted to give daily use values in line with the MTP trends, which show that oven use has fallen from 1.6 use events per day to a current value of 0.5 (for example, Figure 6-9).

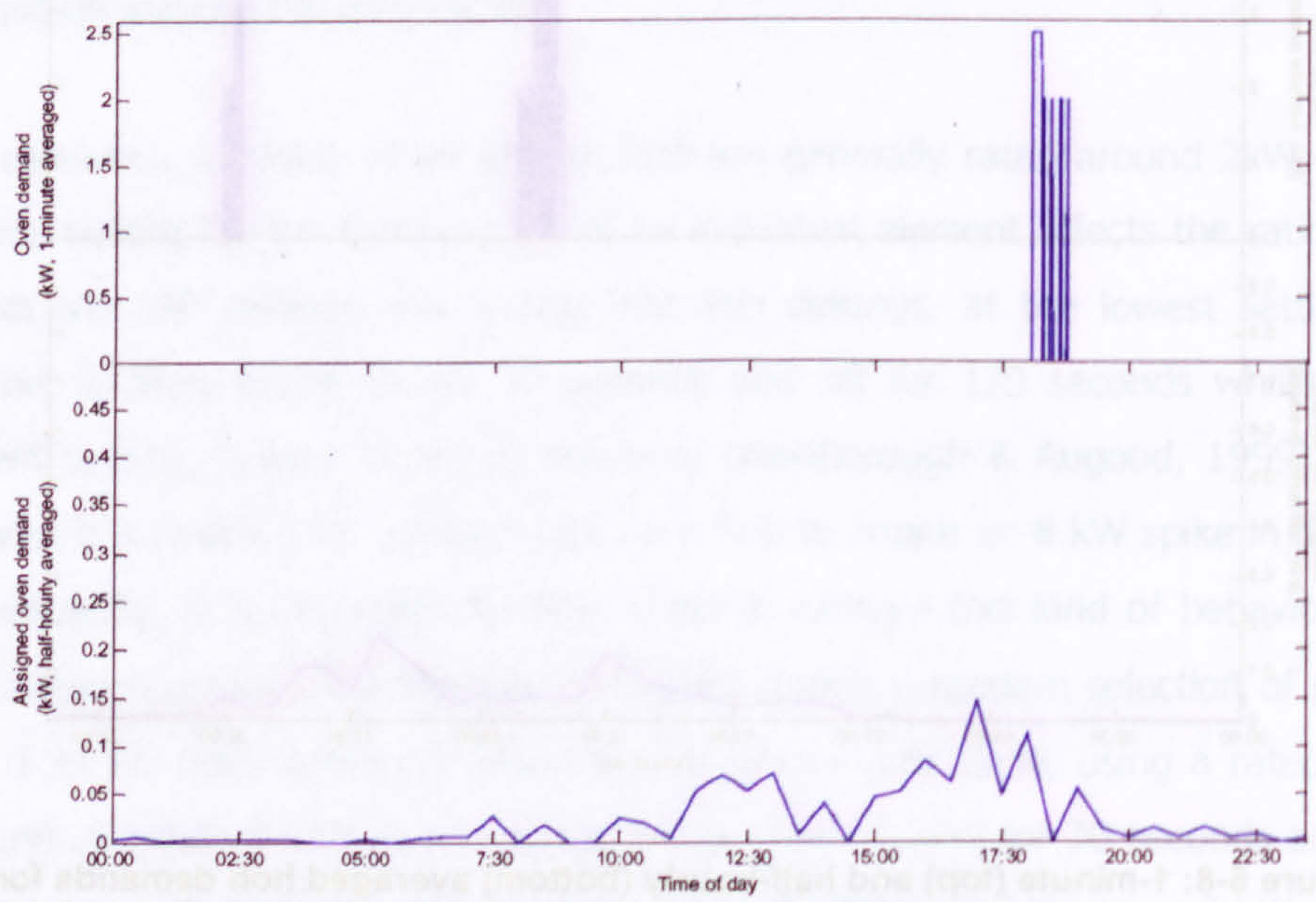


Figure 6-9: 1-minute (top) and half-hourly (bottom) averaged oven demands for a domestic consumer (2 occupants, 21st December, 2005)

6.5.3 *Microwave demand at the 1-minute level*

Microwave ovens usually have a peak rating for cooking of 0.8-0.9 kW. Most models offer a range of up to five different power levels for cooking although typically the lower settings are used for defrosting and the highest for cooking. Some are also fitted with turntables and grills which take the maximum rated power to a typical value of 1.3kW. Increasingly microwaves are being built as combined appliances including a conventional oven. Since digital timer controls are more frequently used with microwave ovens, clocks are generally a built in feature.

For the model, it is assumed that a microwave will use 0.005 kW continuously, representing the standby consumption. This is deducted from the assigned half-hourly demand for the purposes of triggering events. It is assumed that during a cooking event, the power will remain constant at a level selected randomly from two different settings (assumed to be either 0.22 kW for defrosting or 1.30 kW for cooking or warming up food). The duration depends on the setting selected, with differing distributions for each (detailed further in Appendix E). The probability of an event occurring is calculated by dividing the assigned half-hourly microwave demand by the product of the rated power and the event duration, adjusted by a scaling factor. The latter has been determined to give an average daily use of around 7 minutes for cooking/warming-up and 5.5 minutes for defrosting which is based on figures in Mansouri et al's study [Mansouri et al, 1996]. Typically just over two events are triggered per day (Figure 6.10)

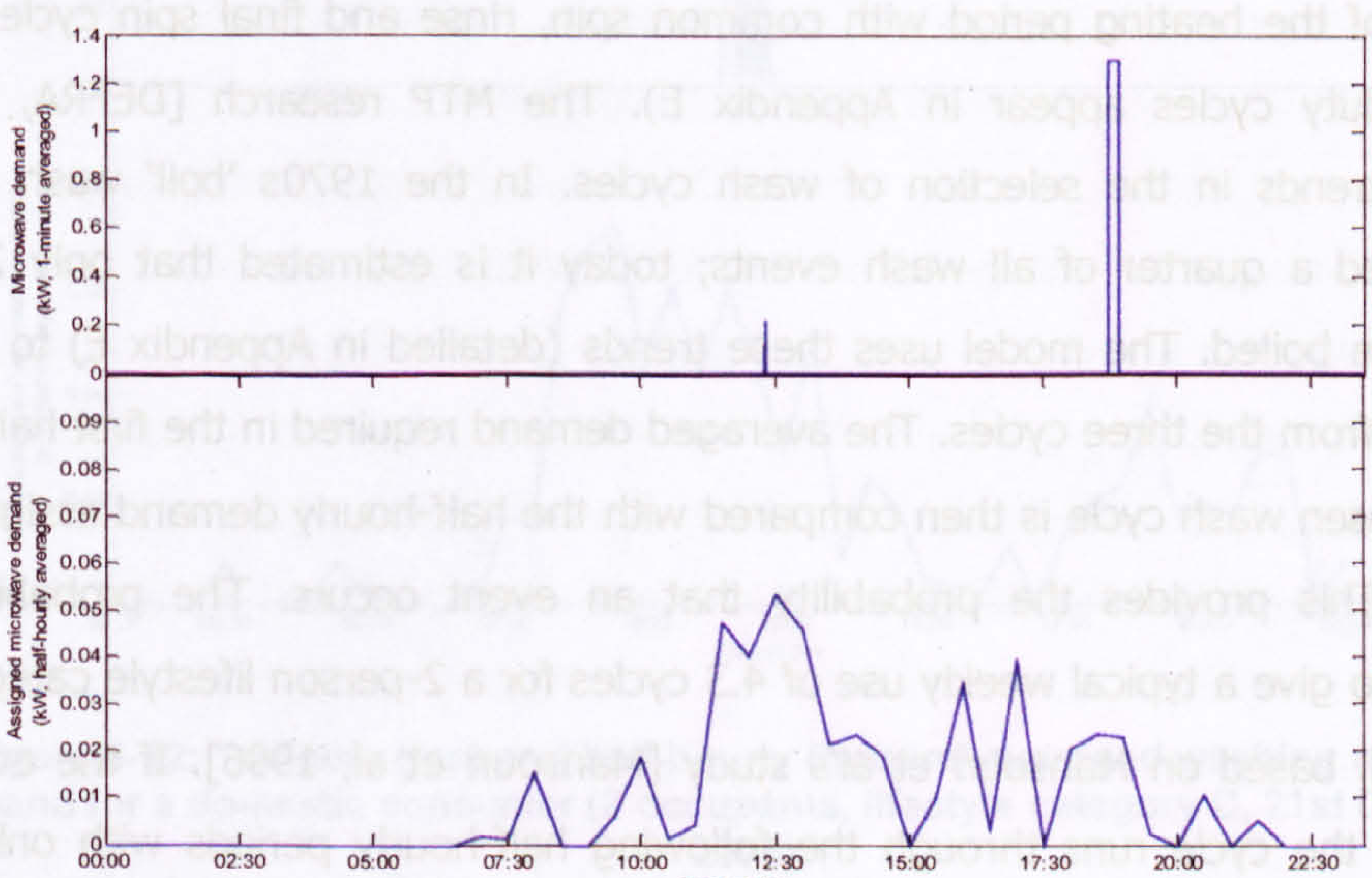


Figure 6-10: 1-minute (top) and half-hourly (bottom) averaged microwave demands for a domestic consumer (2 occupants, 21st December, 2005)

6.5.4 Kettle demand at the 1-minute level

A description of how the model calculates kettle demand at the 1-minute averaged level was given earlier as an example in section 6.1.2. For a 2-person household, in 1996, the model estimates a typical daily usage of 3.3 events per day (compared to an estimated 3.2 from the DECADE study [Boardman et al, 1994]) with a range of 0-10 daily events (compared to 3-15 uses per day from Newborough & Augood's study [Newborough & Augood, 1999]).

6.6 Washing appliance demand – 1-minute specific

6.6.1 Washing machine demand at the 1-minute level

A large part of the washing machine demand is created by a heating phase, the duration of which depends on the wash cycle selected (usually based on the final wash temperature) and the temperature of the incoming water supply. Typically heating elements have a power rating of around 2 kW. Pumps, spin motors and controls create further demand, usually peaking at around 0.75 kW, based on the study by Newborough and Augood [Newborough & Augood, 1999]. The complete wash cycle generally lasts between 50 to 90 minutes.

The model uses three different duty cycles for the detailed washing machine demand: 40°, 60° and 90° ('warm', 'hot' and 'boil' washes, Figure 6-11). To simplify the duty cycle, it is assumed that the difference between the cycles lies in the duration of the heating period with common spin, rinse and final spin cycles (the detailed duty cycles appear in Appendix E). The MTP research [DEFRA, 2001] provides trends in the selection of wash cycles. In the 1970s 'boil' wash cycles represented a quarter of all wash events; today it is estimated that only 2% of clothes are boiled. The model uses these trends (detailed in Appendix E) to select randomly from the three cycles. The averaged demand required in the first half-hour of the chosen wash cycle is then compared with the half-hourly demand assigned in layer 2. This provides the probability that an event occurs. The probability is adjusted to give a typical weekly use of 4.3 cycles for a 2-person lifestyle category C household, based on Mansouri et al's study [Mansouri et al, 1996]. If the event is triggered, the cycle runs through the following half-hourly periods with only one cycle permitted in any half-hour (Figure 6-12).

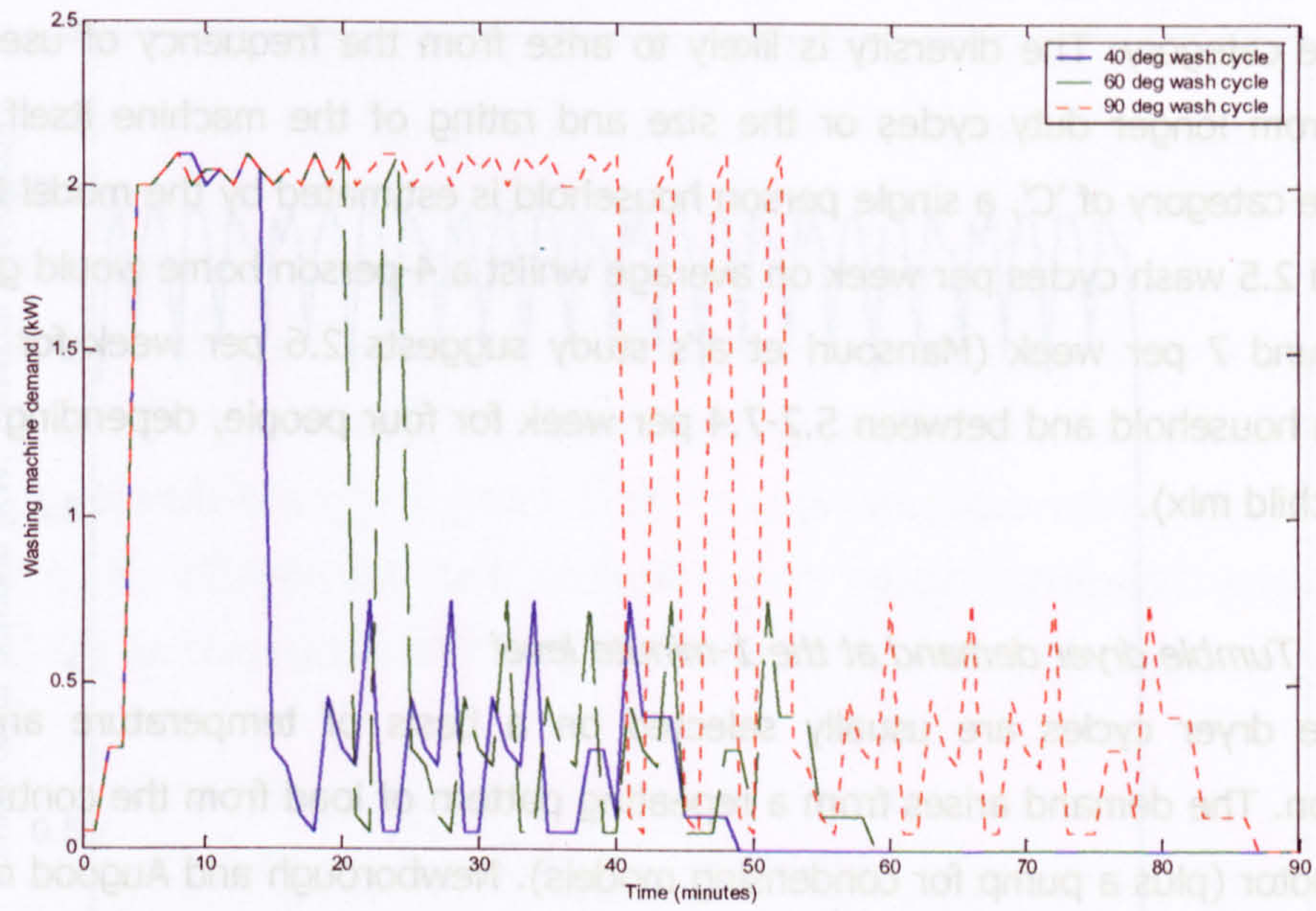


Figure 6-11: Three washing machine duty cycles used in the model showing the variation in demand on a 1-minute averaged basis

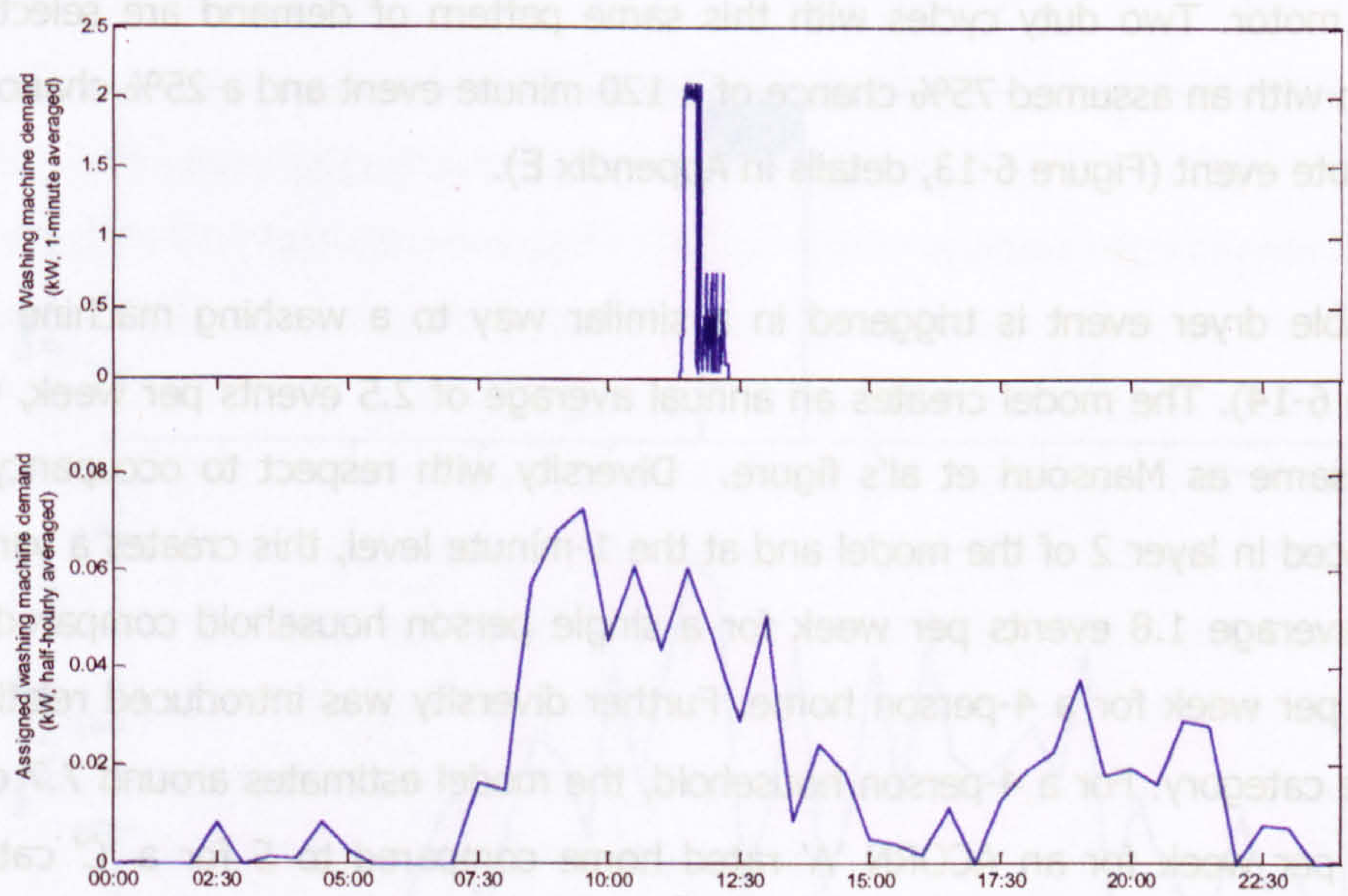


Figure 6-12: 1-minute (top) and half-hourly (bottom) averaged washing machine demand for a domestic consumer (2 occupants, lifestyle category C, 21st December, 2005)

In layer 2, washing machine demand is diversified in relation to occupancy and lifestyle category. The diversity is likely to arise from the frequency of use rather than from longer duty cycles or the size and rating of the machine itself. For a lifestyle category of 'C', a single person household is estimated by the model to have around 2.5 wash cycles per week on average whilst a 4-person home would give rise to around 7 per week (Mansouri et al's study suggests 2.6 per week for a one-person household and between 5.2-7.4 per week for four people, depending on the adult/child mix).

6.6.2 Tumble dryer demand at the 1-minute level

Tumble dryer cycles are usually selected on a basis of temperature and total duration. The demand arises from a repeating pattern of load from the controls and spin motor (plus a pump for condensing models). Newborough and Augood report a typical peak demand of 2.5kW and the MTP a typical duty cycle demand of 3.5 kWh (for appliances before 2000). Based on this information and on observations of an Ariston washer dryer in tumble dry mode, the model uses an assumed appliance duty cycle that includes a continuous demand of 0.05 kW for controls and 1.75 kW for a heater and fan and intermittent demands of 0.8kW for a pump and 1.5 kW for a spin motor. Two duty cycles with this same pattern of demand are selected at random with an assumed 75% chance of a 120 minute event and a 25% chance of a 90 minute event (Figure 6-13, details in Appendix E).

A tumble dryer event is triggered in a similar way to a washing machine event (Figure 6-14). The model creates an annual average of 2.5 events per week, which is the same as Mansouri et al's figure. Diversity with respect to occupancy was introduced in layer 2 of the model and at the 1-minute level, this creates a variation of an average 1.8 events per week for a single person household compared to 5 events per week for a 4-person home. Further diversity was introduced relating to lifestyle category. For a 4-person household, the model estimates around 7.7 drying events per week for an ACORN 'A' rated home compared to 5 for a 'C' category home.

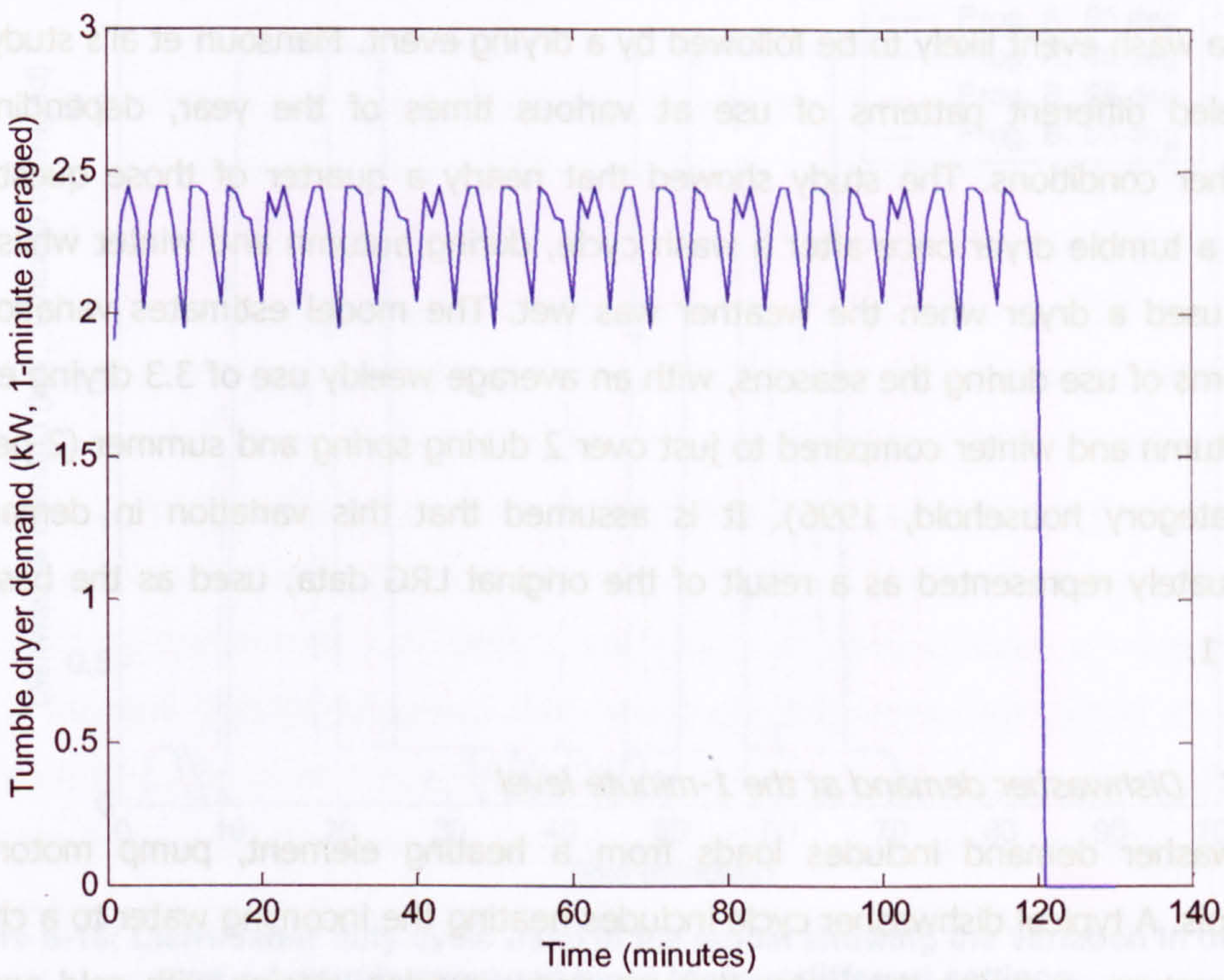


Figure 6-13: Tumble dryer duty cycle used in the model showing the variation in demand on a 1-minute averaged basis

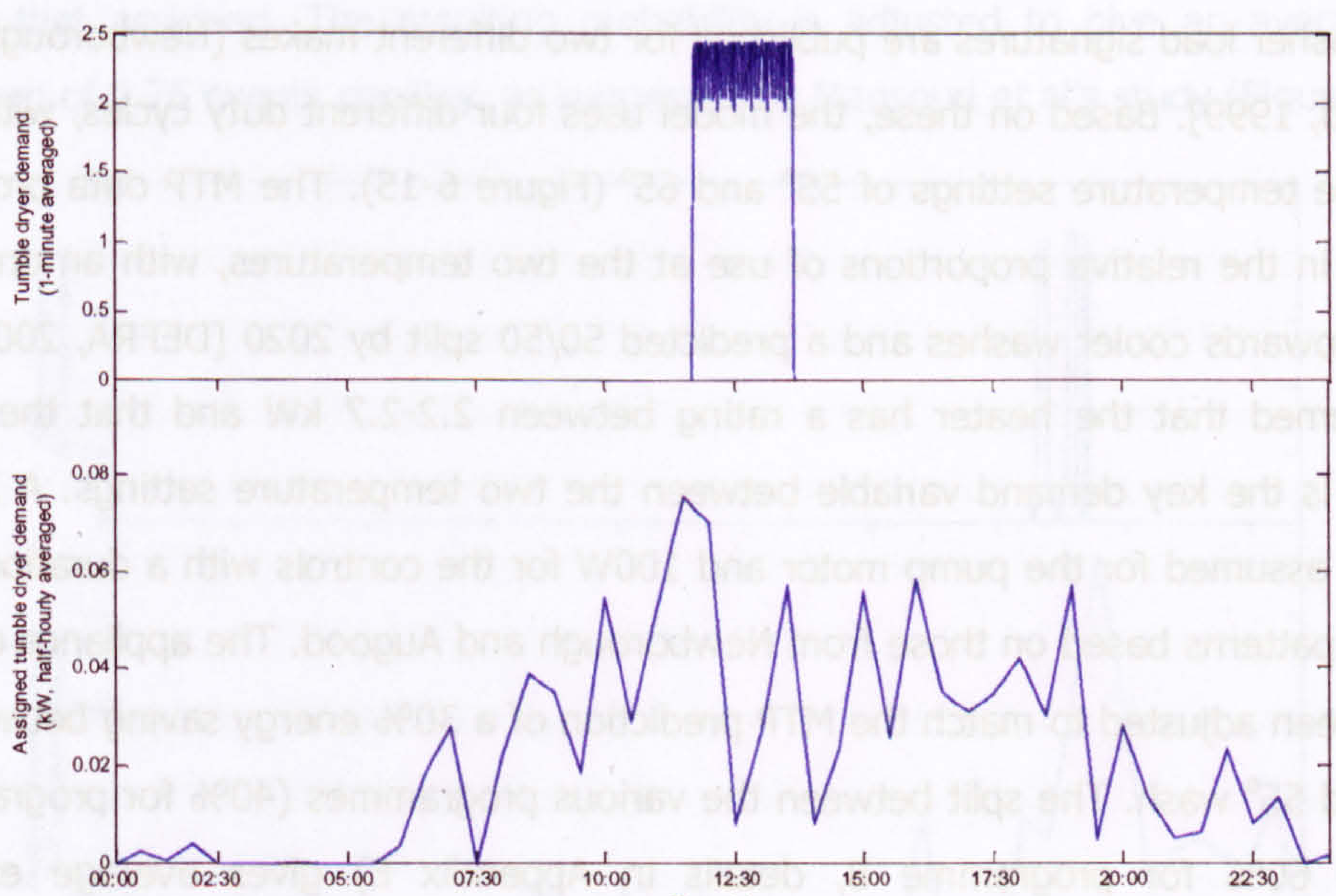


Figure 6-14: 1-minute (top) and half-hourly (bottom) averaged tumble dryer demand for a domestic consumer (2 occupants, lifestyle category C, 21st December, 2005)

In reality, the use of a washing machine and tumble dryer would probably be linked, with a wash event likely to be followed by a drying event. Mansouri et al's study also revealed different patterns of use at various times of the year, depending on weather conditions. The study showed that nearly a quarter of those questioned used a tumble dryer once after a wash cycle, during autumn and winter whilst half only used a dryer when the weather was wet. The model estimates variations in patterns of use during the seasons, with an average weekly use of 3.3 drying events in autumn and winter compared to just over 2 during spring and summer (2-person, 'C' category household, 1996). It is assumed that this variation in demand is adequately represented as a result of the original LRG data, used as the basis for layer 1.

6.6.3 Dishwasher demand at the 1-minute level

Dishwasher demand includes loads from a heating element, pump motor and controls. A typical dishwasher cycle includes heating the incoming water to a chosen temperature, pumping the water through spray nozzles, rinsing with cold and hot water and, in some models, a warm air drying phase. Dishwasher programmes are generally varied in terms of the duration and the temperature.

Dishwasher load signatures are published for two different makes [Newborough and Augood, 1999]. Based on these, the model uses four different duty cycles, with two possible temperature settings of 55° and 65° (Figure 6-15). The MTP data provides trends in the relative proportions of use at the two temperatures, with an ongoing trend towards cooler washes and a predicted 50/50 split by 2020 [DEFRA, 2001]. It is assumed that the heater has a rating between 2.2-2.7 kW and that the heat period is the key demand variable between the two temperature settings. A 200W load is assumed for the pump motor and 100W for the controls with a duration and timing patterns based on those from Newborough and Augood. The appliance cycles have been adjusted to match the MTP prediction of a 30% energy saving between a 65° and 55° wash. The split between the various programmes (40% for programme A and 60% for programme B, details in Appendix E) gives average energy consumption per event of 1.5 kWh, which matches the data from the DECADE study [Boardman et al, 1994].

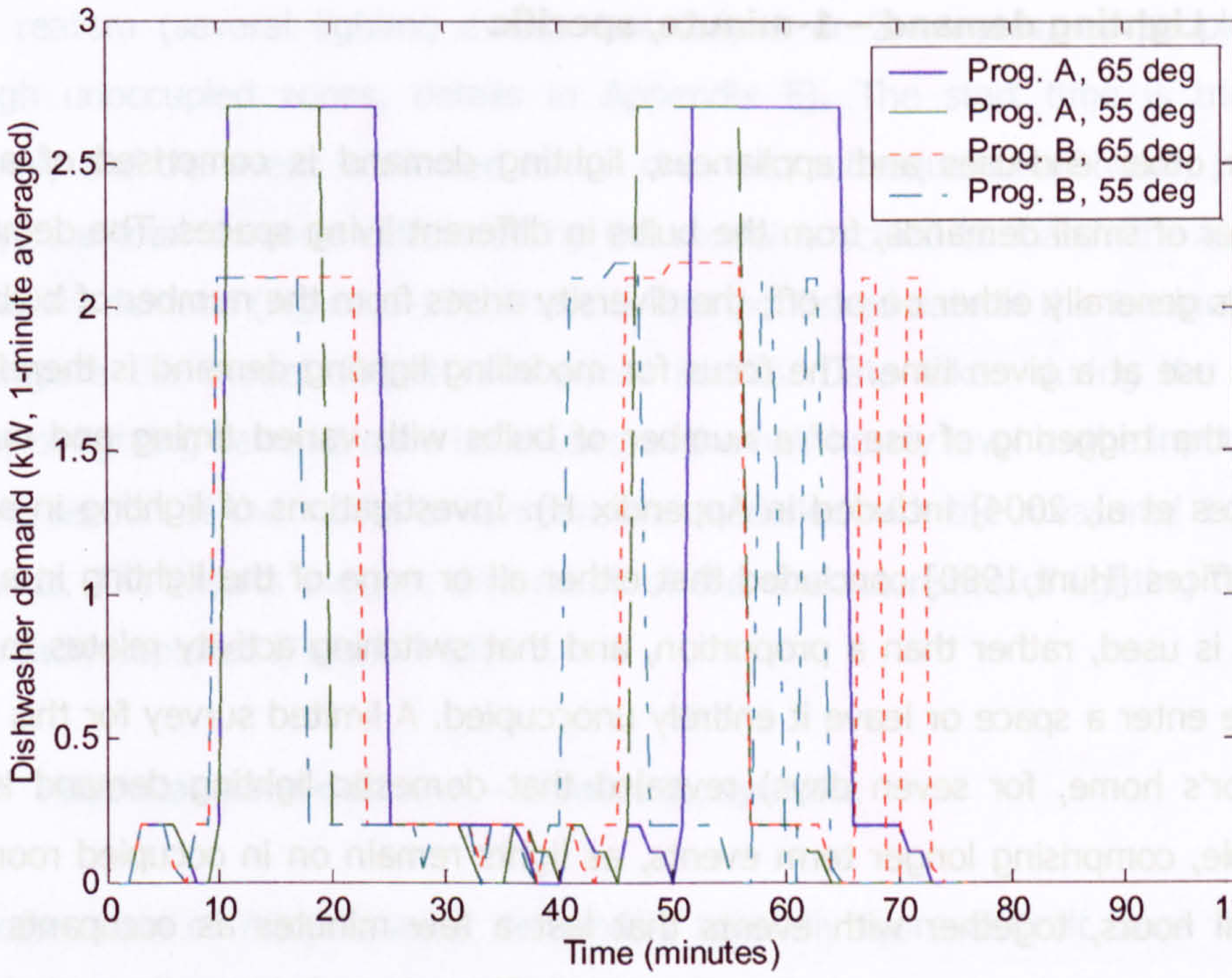


Figure 6-15: Dishwasher duty cycle used in the model showing the variation in demand on a 1-minute averaged basis for four different settings

As for the other washing appliances, dishwasher events are triggered by comparing the average demand for the selected dishwasher programme in the first half-hour with that assigned. The resulting probability is adjusted to give an average use pattern of 0.76 events per day, as suggested by Mansouri et al's study (Figure 6-16).

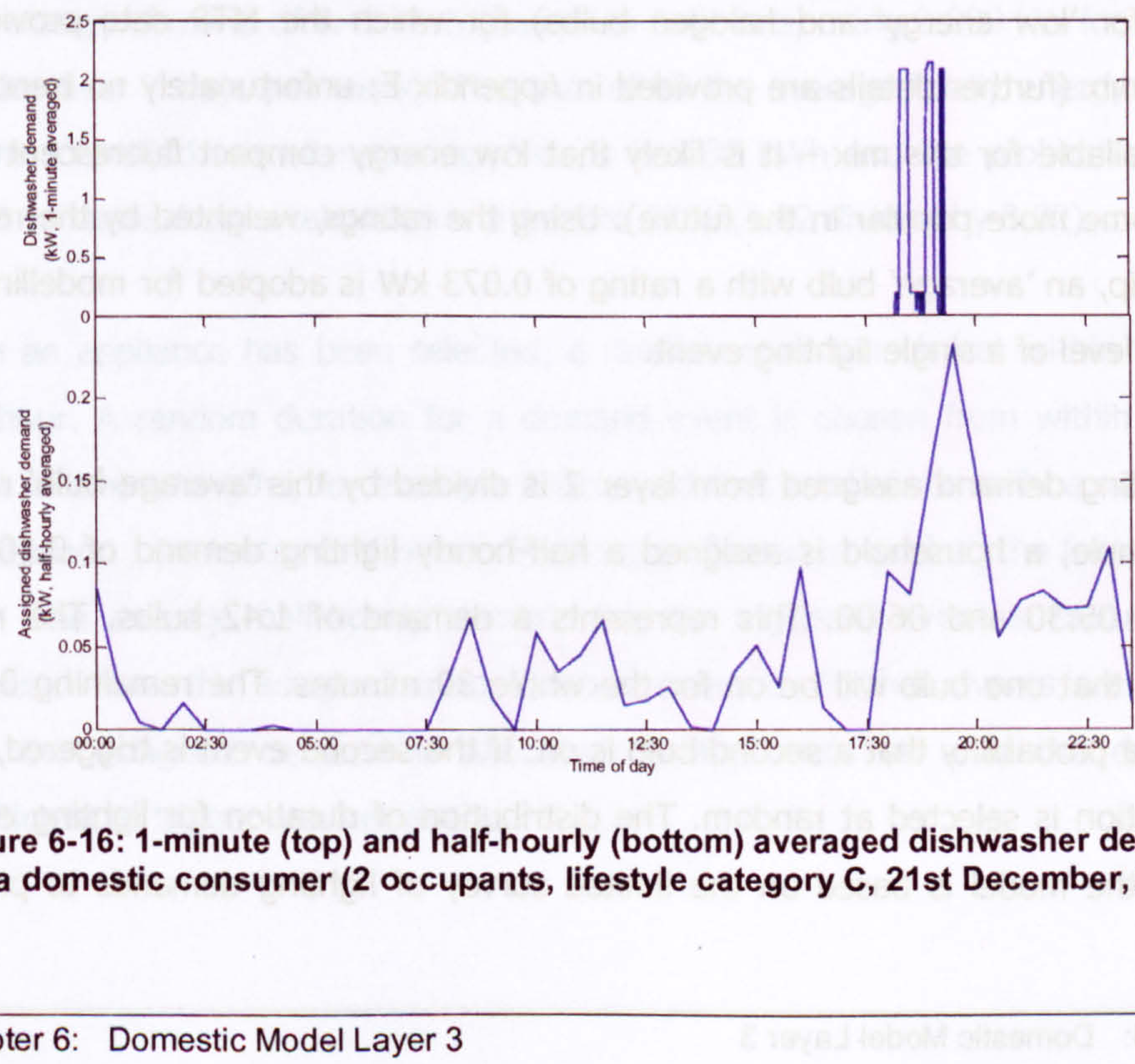


Figure 6-16: 1-minute (top) and half-hourly (bottom) averaged dishwasher demand for a domestic consumer (2 occupants, lifestyle category C, 21st December, 2005)

6.7 Lighting demand – 1-minute, specific

Unlike other end-uses and appliances, lighting demand is comprised of a large number of small demands, from the bulbs in different living spaces. The demand of each is generally either on or off; the diversity arises from the number of bulbs that are in use at a given time. The focus for modelling lighting demand is therefore to allow the triggering of use of a number of bulbs with varied timing and duration ([Stokes et al, 2004] included in Appendix H). Investigations of lighting in schools and offices [Hunt,1980] concluded that either all or none of the lighting in a given space is used, rather than a proportion, and that switching activity relates to when people enter a space or leave it entirely unoccupied. A limited survey for this model (author's home, for seven days) revealed that domestic lighting demand is very variable, comprising longer term events, as lights remain on in occupied rooms for several hours, together with events that last a few minutes as occupants move through spaces that are generally unoccupied. There is a slight positive relationship between the number of lights being switched on and the demand in a given half-hour (since both relate to higher levels of occupancy and/or activity).

Whilst there is some diversity arising from the bulb ratings, the model simplifies the calculation by assuming that all lighting events use a standard bulb. Bulbs are available at several power ratings (typically 40W, 60W and 100W but also smaller ratings for 'low energy' and halogen bulbs) for which the MTP data provides a relative mix (further details are provided in Appendix E; unfortunately no trend data were available for this mix – it is likely that low energy compact fluorescent bulbs will become more popular in the future). Using the ratings, weighted by the relative ownership, an 'average' bulb with a rating of 0.073 kW is adopted for modelling the demand level of a single lighting event.

The lighting demand assigned from layer 2 is divided by this 'average bulb' rating. For example, a household is assigned a half-hourly lighting demand of 0.104 kW between 05:30 and 06:00. This represents a demand of 1.42 bulbs. The model assumes that one bulb will be on for the whole 30 minutes. The remaining 0.42 is used as a probability that a second bulb is on. If the second event is triggered, then the duration is selected at random. The distribution of duration for lighting events used in the model is based on the limited survey of lighting demands to provide more realism (several lighting events last only 1 or 2 minutes, as people pass through unoccupied zones, details in Appendix E). The start time is triggered randomly and the event is allowed to run over into subsequent half-hourly periods. Finally, the total demand calculated by the model is scaled to match the assigned half-hourly demand (Figure 6-17). There is little published data at the 1-minute level to compare the model output with actual results. Data taken during the limited survey of lighting demand have been used at the half-hourly level as the input to the lighting section of the model to compare the modelled with the measured 1-minute demands. The results suggest that many of the characteristics of lighting demand are broadly captured (Figure 6-18).

6.8 Miscellaneous demand – 1-minute, specific

The estimation of miscellaneous demand is naturally more difficult since it arises from unknown appliances with a variety of ratings and use patterns. In the model, a random selection is made of demand from twenty-one of the more significant household appliances. These include televisions, hi-fi systems, computers and peripherals together with small appliances for cooking, cleaning and personal care. The distribution for the random selection is based on the average daily energy used by each appliance which is calculated from an assumed daily and weekly use pattern and typical power ratings. For example, a television is assumed to have an average daily energy demand of 1.42 kWh (based on 2.44 sets, using 0.090 kW for 6.5 hours per day over 7 days per week). The sum of all the averaged daily energy demands for the identified miscellaneous appliances is 3.82 kWh and the probability that an event will arise from a television is therefore 37% (1.42 divided by 3.82).

Once an appliance has been selected, a random start time is set within the given half-hour. A random duration for a demand event is chosen from within a typical range of event lengths, for example it assumed that a television will be switched on for between 15 minutes to 4 hours. Events are allowed to run into the following half-hour. The average half-hourly demand for the triggered event is calculated and deducted from the assigned miscellaneous demand. Further events are triggered until the assigned demand is allocated to appliances or until the demand is insufficient to trigger another event.

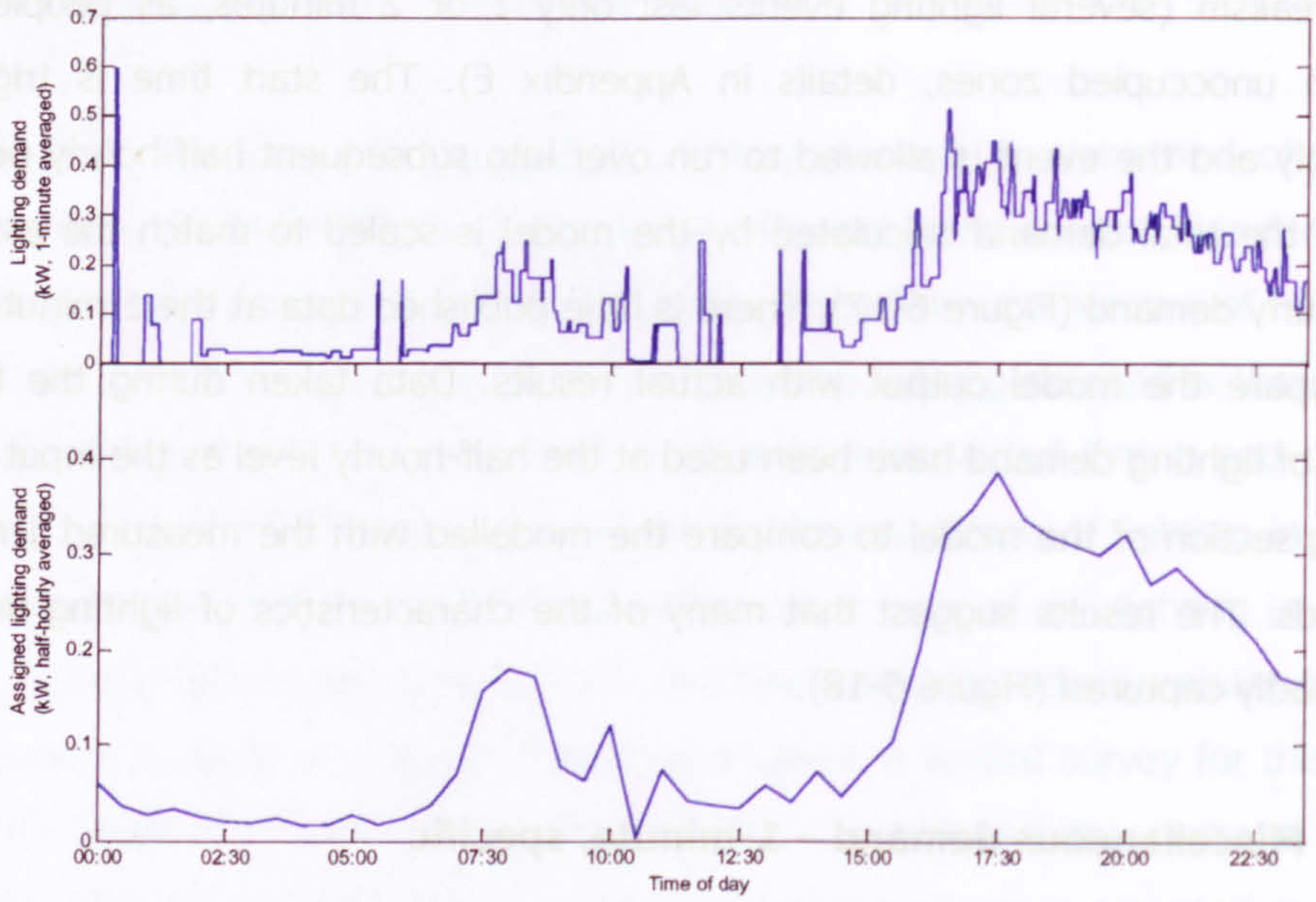


Figure 6-17: 1-minute (top) and half-hourly (bottom) averaged lighting demand for a domestic consumer (2 occupants, lifestyle category C, 21st December, 2005)

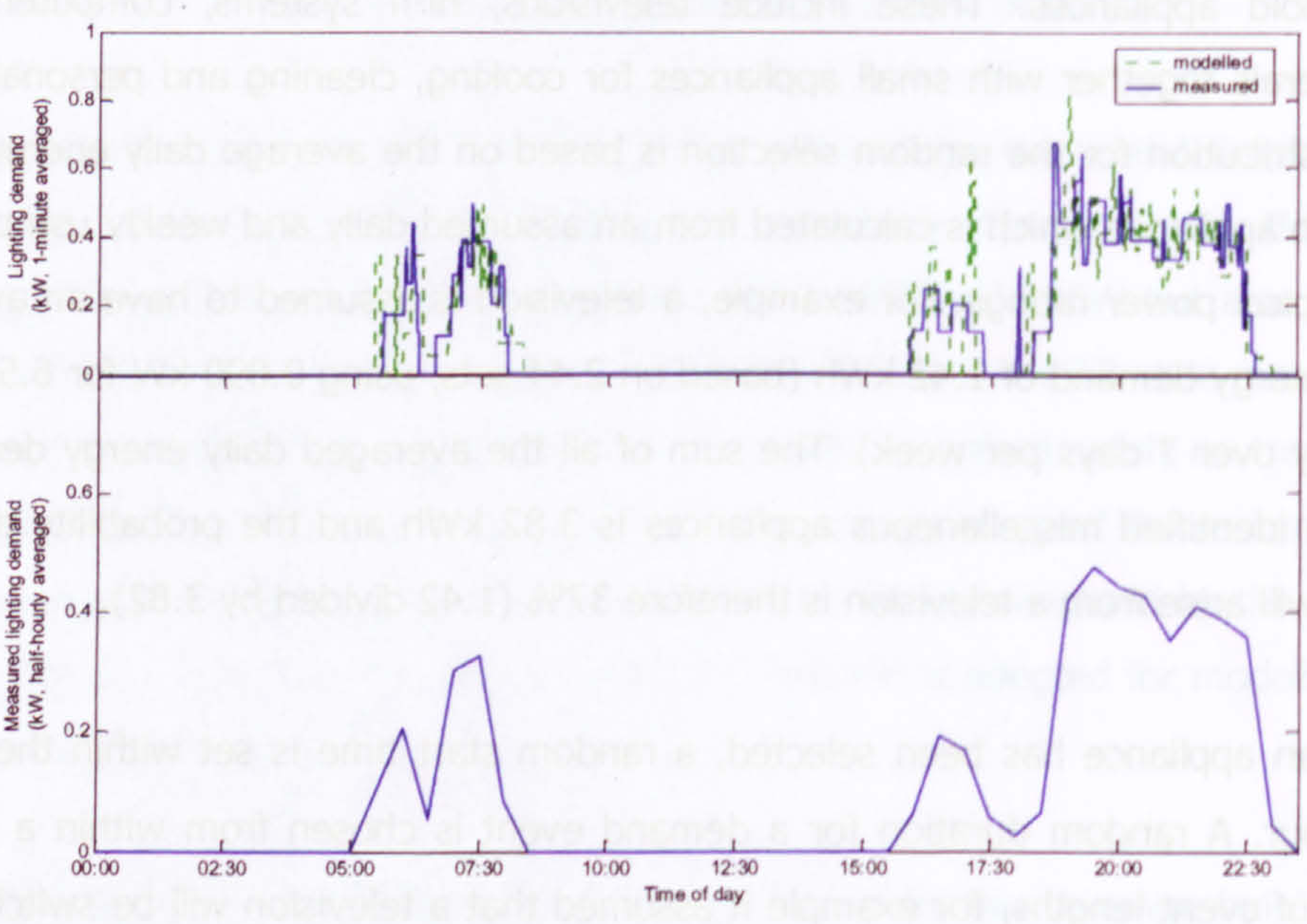


Figure 6-18: Comparison of modelled and measured lighting demand (top) at the 1-minute level, based on measured half-hourly averaged demand (bottom) (4-person house, above average income, 2nd April, 2003)

When the remaining demand falls below 0.005 kW, no further events are triggered and a standby demand of 5W is assumed to run throughout the half-hourly period. The appliance events are also modelled as a constant power demand throughout the chosen duration (further details of the miscellaneous demand 1-minute model appear in Appendix E). The miscellaneous demand is the sum of all the individual appliance events triggered (Figure 6-19).

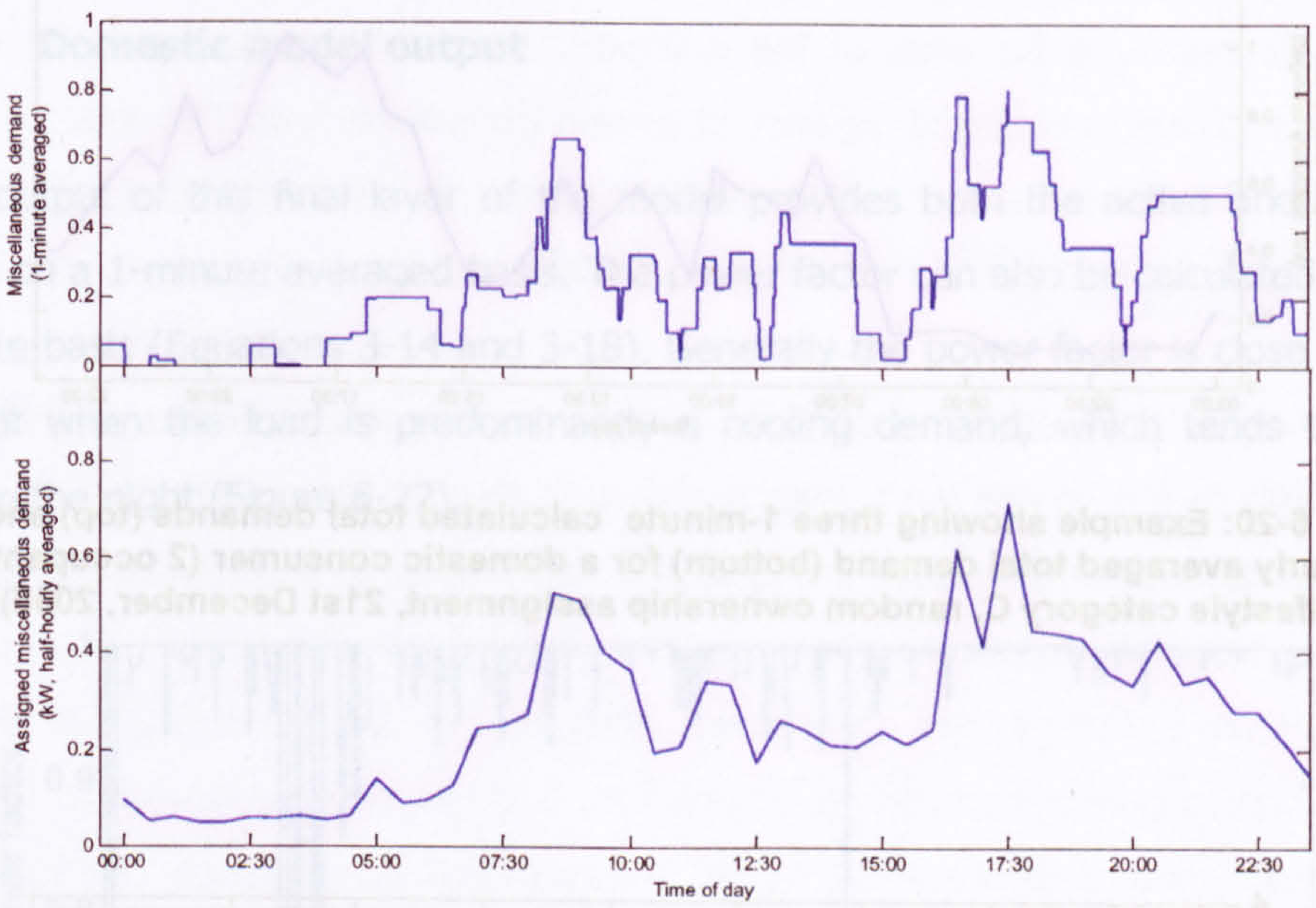


Figure 6-19: 1-minute (top) and half-hourly (bottom) averaged miscellaneous demand for a domestic consumer (2 occupants, lifestyle category C, 21st December, 2005)

6.9 Total demand – 1-minute, specific

6.9.1 Total active demand

The total active demand (of which the components have been described in the preceding sections) is simply the sum of all the 1-minute demands created by the individual end-uses and appliances (Equation 3-15). Due to the random nature in which the appliance events are triggered, the total demand at this level will be very variable (Figure 6-20). The modelled data appear to capture similar demand characteristics to those found in measured data (Figure 6-21). Chapter 8 looks in more depth at the comparison between the domestic model output and two sets of measured data.

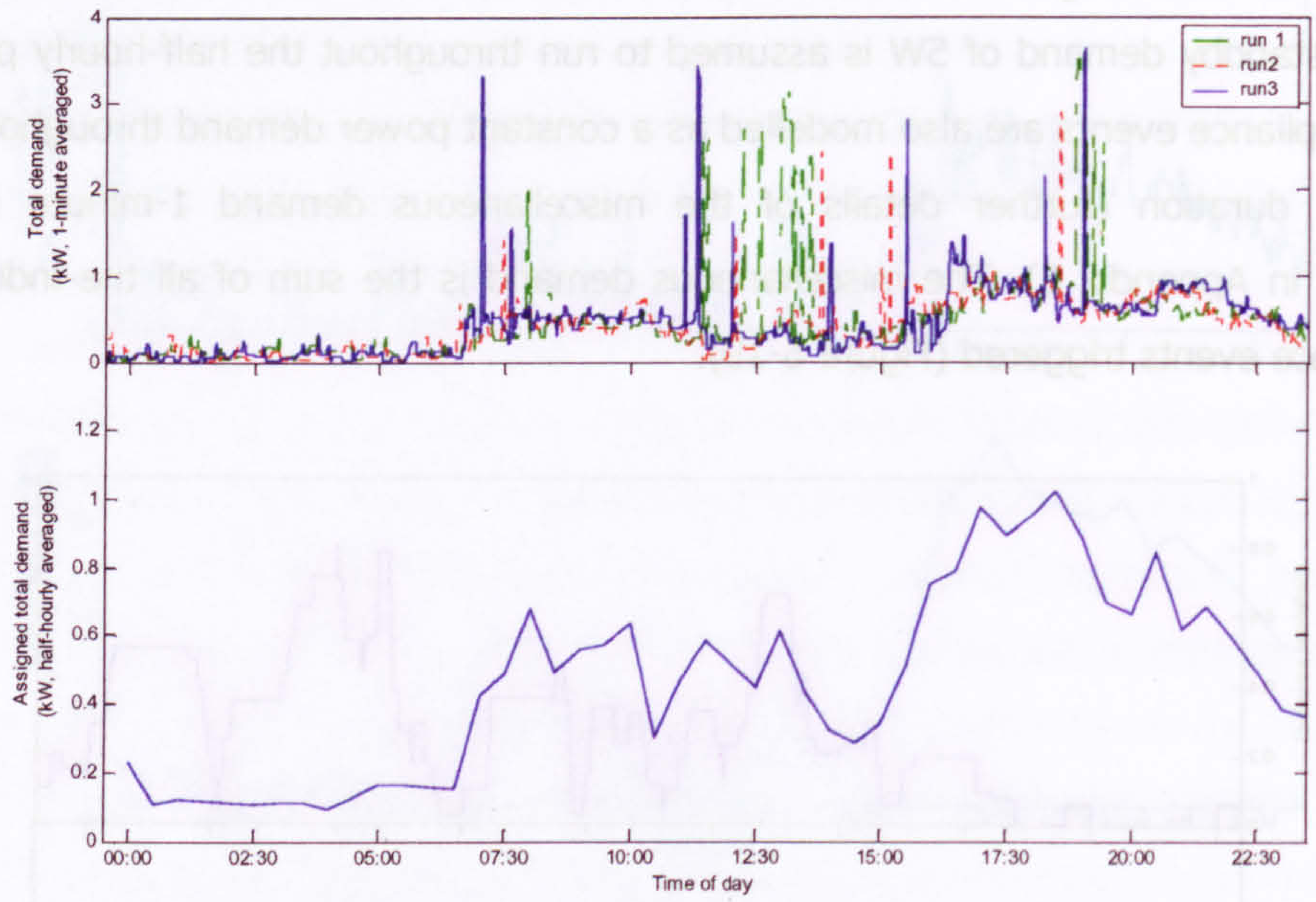


Figure 6-20: Example showing three 1-minute calculated total demands (top) and half-hourly averaged total demand (bottom) for a domestic consumer (2 occupants, lifestyle category C, random ownership assignment, 21st December, 2005)

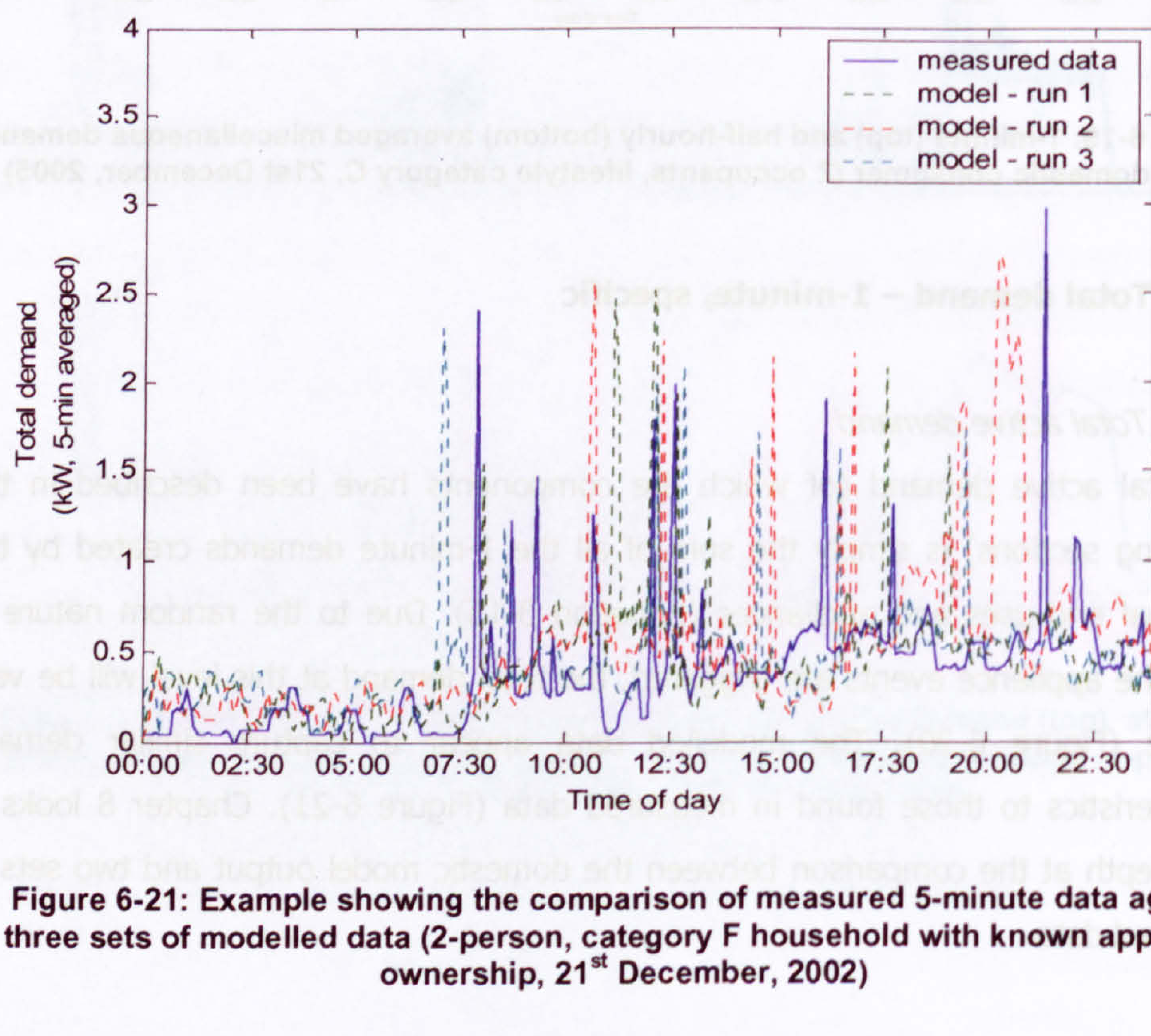


Figure 6-21: Example showing the comparison of measured 5-minute data against three sets of modelled data (2-person, category F household with known appliance ownership, 21st December, 2002)

6.9.2 Total reactive demand

The reactive demands for each end-use/appliance are calculated using power factors (Equations 3-13 and 3-14). A power factor value of 1.0 is used for most of the demands. Cooling appliances are assumed to have a power factor of 0.7 and washing appliances are assumed to have a power factor of 0.9 during the spin cycle [Newborough and Augood, 1999].

6.10 Domestic model output

The output of this final layer of the model provides both the active and reactive loads on a 1-minute averaged basis. The power factor can also be calculated on a 1-minute basis (Equations 3-14 and 3-18). Generally the power factor is close to unity except when the load is predominantly a cooling demand, which tends to occur during the night (Figure 6-22).

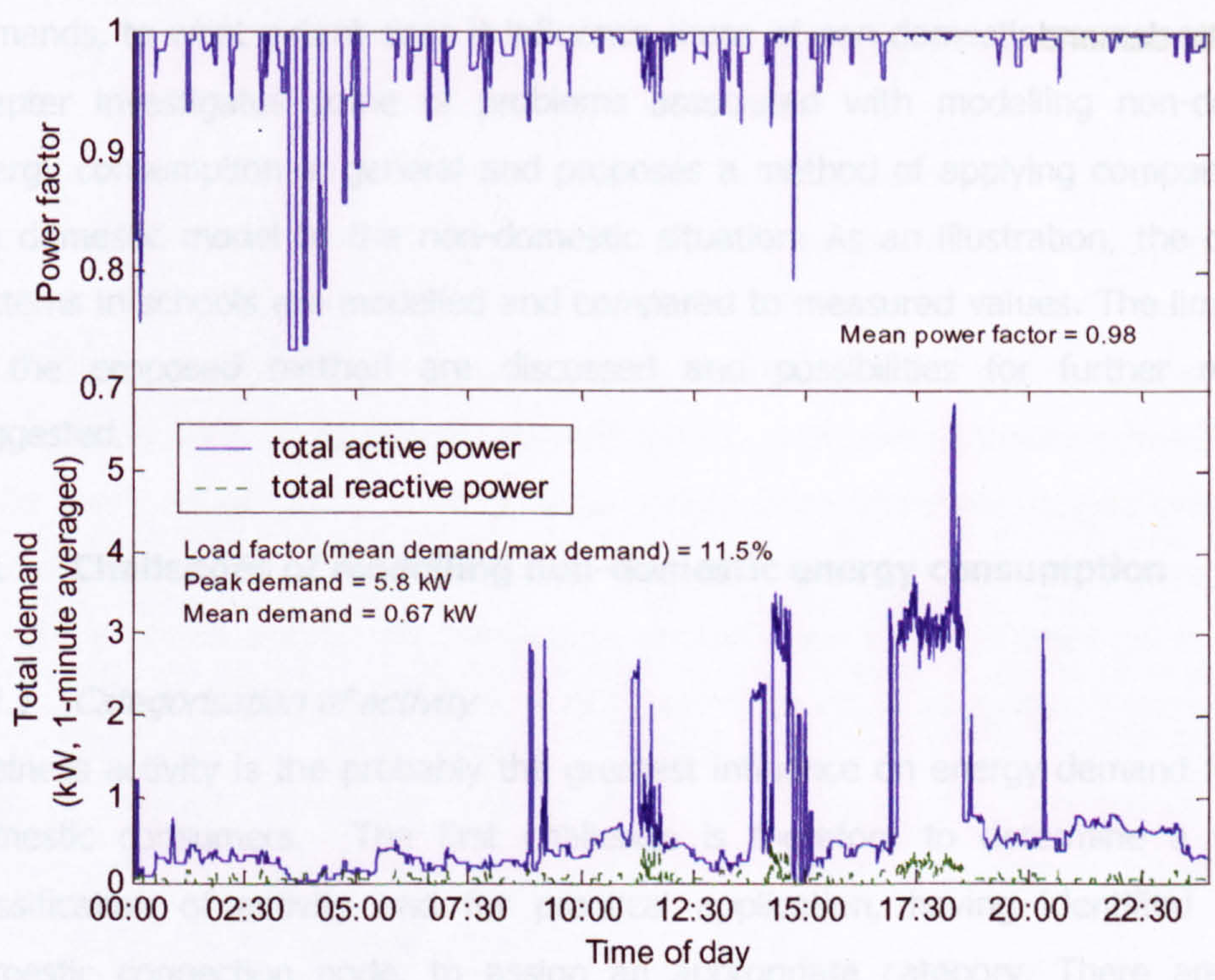


Figure 6-22: Example showing the power factor (top) and the 1-minute averaged active and reactive loads (bottom) calculated for one run of the domestic model (2-person, category F household with known appliance ownership, 21st December, 2002)

6.10 Summary: Chapter 6

Layer 3 of the domestic model has to match the diversity factors introduced in layer 2. This matching depends on the detailed way in which different appliances are used (i.e. higher assigned demand can equate with a higher appliance rating and/or longer periods or increased frequency of use). The detailed application of the underlying concepts, using the half-hourly assigned demand to trigger appliance events, is described for each of the end-uses. For each, comparisons are made, where data have been found, against measured patterns of use. The total 1-minute demand (active and reactive components) provide a more diverse and spiky profile which begins to resemble the reality of individual demands.

This concludes the detailed description of the domestic model. Before investigating the validity of this model in Chapter 8, the next chapter looks at the way in which parts of the domestic model are adapted to provide a representation of non-domestic demand.

Chapter

7

Non-Domestic Demand

An institution is the lengthened shadow of one man
Ralph Waldo Emerson

If the sun provides the underlying framework of our domestic electricity demands, to what extent does it influence those of non-domestic consumers? This chapter investigates some of problems associated with modelling non-domestic energy consumption in general and proposes a method of applying components of the domestic model to the non-domestic situation. As an illustration, the demand patterns in schools are modelled and compared to measured values. The limitations of the proposed method are discussed and possibilities for further research suggested.

7.1 Challenges of modelling non-domestic energy consumption

7.1.1 Categorisation of activity

Business activity is the probably the greatest influence on energy demand for non-domestic consumers. The first challenge is therefore to determine a suitable classification of activity and for practical application, having identified a non-domestic connection node, to assign an appropriate category. There are many different methods of classifying non-domestic properties, the most common being the Standard Industrial Classification of Economic Activities (SIC) scheme, which is widely used in the UK [National Statistics, 2002]. An alternative system is provided by the UK's Valuation Office [VO, 2004], who offer a useful resource for identifying appropriate categories (both for single and mixed use properties) for specific connection nodes and Address Points on a GIS. The work of the NBDS included the derivation of a classification system that was compatible with both [Mortimer et al, 2000] and this gives a useful basis for grouping organisations with broadly similar energy demands and use patterns. The NBDS provide energy consumption data for 32 different categories of non-domestic consumer [Elsayed et al, 2002] based on a survey of non-domestic consumers in four typical towns in the UK.

7.1.2 Variations in energy consumption

The most common method of simplifying energy consumption data for non-domestic premises is to consider the specific consumption in relation to unit floor area. Non-domestic use of buildings often involves shared occupation and the split in the area occupied between different consumers is not always obvious. Buildings of unusual shape or of highly varied use, such as shopping malls, where car parks, shops, cinemas, etc. are mixed together, present an especially difficult problem. Floor areas can be estimated from plan areas derived from GIS maps or aerial photographs. The Valuation Office database also provides some assistance in this respect.

However, within a given category of activity, the distribution of floor areas can be very skewed over a broad range. For example, the NBDS sample revealed a range in floor areas from 196 to 4995 m^2 (mid-quartile range 1275-3250 m^2) for supermarkets, with a large variation in specific energy demands, between 0.732 to 4.198 GJ/m^2/annum [Elsayed et al, 2002]. Similarly in a study of 7000 retail outlets, comparing annual electricity consumption against floor areas, whilst there was a weak positive correlation between the two factors, the data were highly scattered [Jones et al, 1999(b)]. This was similarly established for schools during a study of public sector buildings in Northern Ireland ([Jones et al, 2004], Figure 7-1).

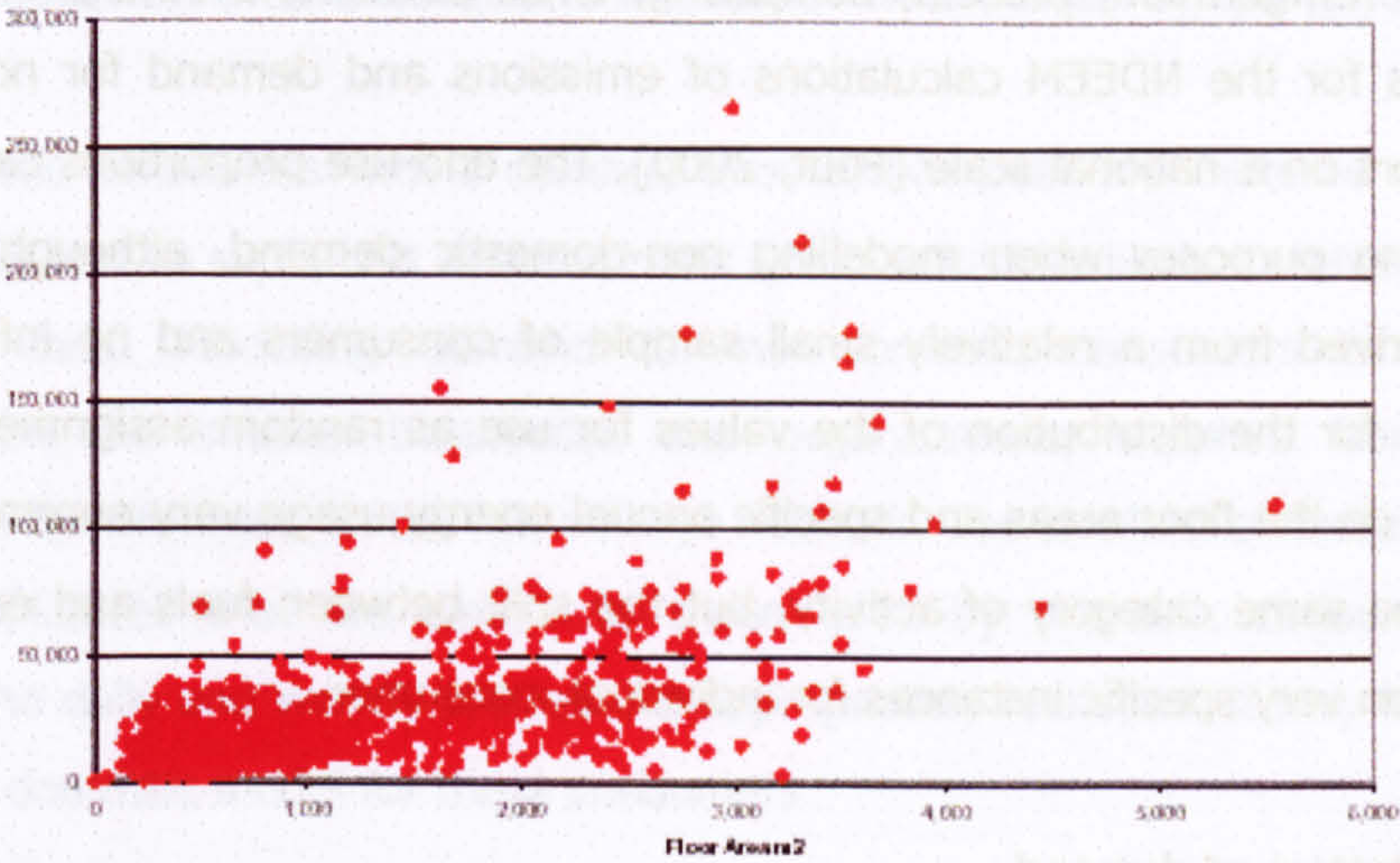


Figure 7-1: Relationship between annual electricity consumption and floor area for a sample of schools in Northern Ireland [Jones et al, 2004]

A comprehensive survey of energy use in offices, generally referred to as EN19 [Action Energy, 2003], provides typical and benchmark values for consumption and costs. The study identities that energy consumption within this single category is affected by key features (e.g. office layout, space cooling), building quality (including basic design and control systems), density of energy use (e.g. spaces with a high intensity of demand, such as for cooking or mainframe computing) and occupancy/management (e.g. hours of occupancy, ratio of occupied/unoccupied space, maintenance).

Clearly, capturing the main elements of diversity is far more complicated for non-domestic consumers, even within a single activity category, than for domestic consumers. An accurate representation of energy demand, in terms of scale alone, would require a much wider range of inputs (or knowledge of their distribution in the case of random selections). Nevertheless, especially in the absence of specific information, estimates of floor area and specific energy consumption, based mainly on the NBDS survey, provide a useful starting point.

7.1.3 Determining the electricity consumption

The NBDS published data [Elsayed, 2002] provide a proportion of the total energy consumed by fuel type (electricity, natural gas and other) and for a variety of end-uses (categorised into space heating and cooling, ventilation, water heating, lighting, catering, refrigeration, process, computing, small power and other). This provides the basis for the NDEEM calculations of emissions and demand for non-domestic consumers on a national scale [Pout, 2000]. The end-use proportions can be useful for scaling purposes when modelling non-domestic demand, although they have been derived from a relatively small sample of consumers and no information is provided for the distribution of the values for use as random assignments. Clearly not only do the floor areas and specific annual energy usage vary enormously, even within the same category of activity, but the split between fuels and end-uses will depend on very specific instances for individual consumer.

7.1.4 Pattern of demand

Given the earlier caveats, estimates of these parameters can provide a very crude estimate of annual end-use demand for the more typical non-domestic consumers. To refine the estimate from an annual to a half-hourly or 1-minute basis requires a definition of the pattern of demand. Such patterns will be even more closely linked to activity – with wide variations in daily, weekly and seasonal profiles.

Extensive studies of electricity demand, conducted in southern Sweden [Norén, 1997], provide an indication of typical daily and weekly patterns of demand for hotels, grocery stores, schools, offices and public health buildings. Although this work applies specifically to Sweden, which enjoys a different climate and culture compared to the UK, specific energy data (demand per m^2) has been compared with the NBDS/NDEEM data and the results are similar (e.g. in Swedish schools, a typical value for the specific annual electricity demand is 64 kWh/m^2/annum compared to 66 kWh/m^2/annum in the UK).

The LRG also measured half-hourly data for a sample of non-domestic consumers, which provided typical weekday profiles for different tariffs and for four different load factors, with activity based on SIC categories (Figure 2-7). However, data on a par with the domestic demand data-set was not available for this research and consequently it was not possible to construct an equivalent model for non-domestic consumers.

7.2 Adaptation of the domestic model for non-domestic demand

Non-domestic consumers with a demand over 100kW peak are metered on a half-hourly basis and as such, it is assumed that DNOs would be likely to have access to measured data. Modelling demand for non-domestic consumers is therefore focussed on the smaller businesses and organisations, supplied from shared distribution transformers on the low voltage network. The smallest of these are likely to use appliances that are similar to those used by domestic consumers and, provided the daily and weekly profiles are appropriately reshaped, it may be realistic to use the domestic model for these consumers.

For non-domestic consumers with demands below the 100kW peak threshold and with equipment somewhat different to domestic appliances, a very simplistic representation of demand may still be possible based on parts of the domestic model. Chapter 4 described how layer 1 of the domestic model consists of sinusoidal annual trends with a Gaussian random component, behaving in a similar way to models of temperature, humidity, etc. This approach was adopted to reduce the influence of occupant activity and thereby simplify the load model. Similarly, for elements of the non-domestic load, weather effects will clearly have influence, such as heating and cooling loads that depend on the external ambient temperature and solar irradiation. On the other hand, annual trends in layer 1 of the model for lighting demand are still affected by the coincidence of domestic activity with sunrise and sunset times. For non-domestic consumers, lighting is more likely to be a fairly constant demand through the day and over the year.

Leaving aside the many exceptions for the time being, it is worthwhile exploring the extent to which the annual trends of layer 1 can be used for the non-domestic demand by scaling the pattern in each half-hour to suit a more appropriate daily or weekly profile. The proposed basis picks up on annual trends from layer 1, borrows scaling and profiling information from the NBDS/NDEEM together with Norén's studies and uses a modified version of layer 3 of the domestic model to create 1-minute averaged demands (Figure 7-2).

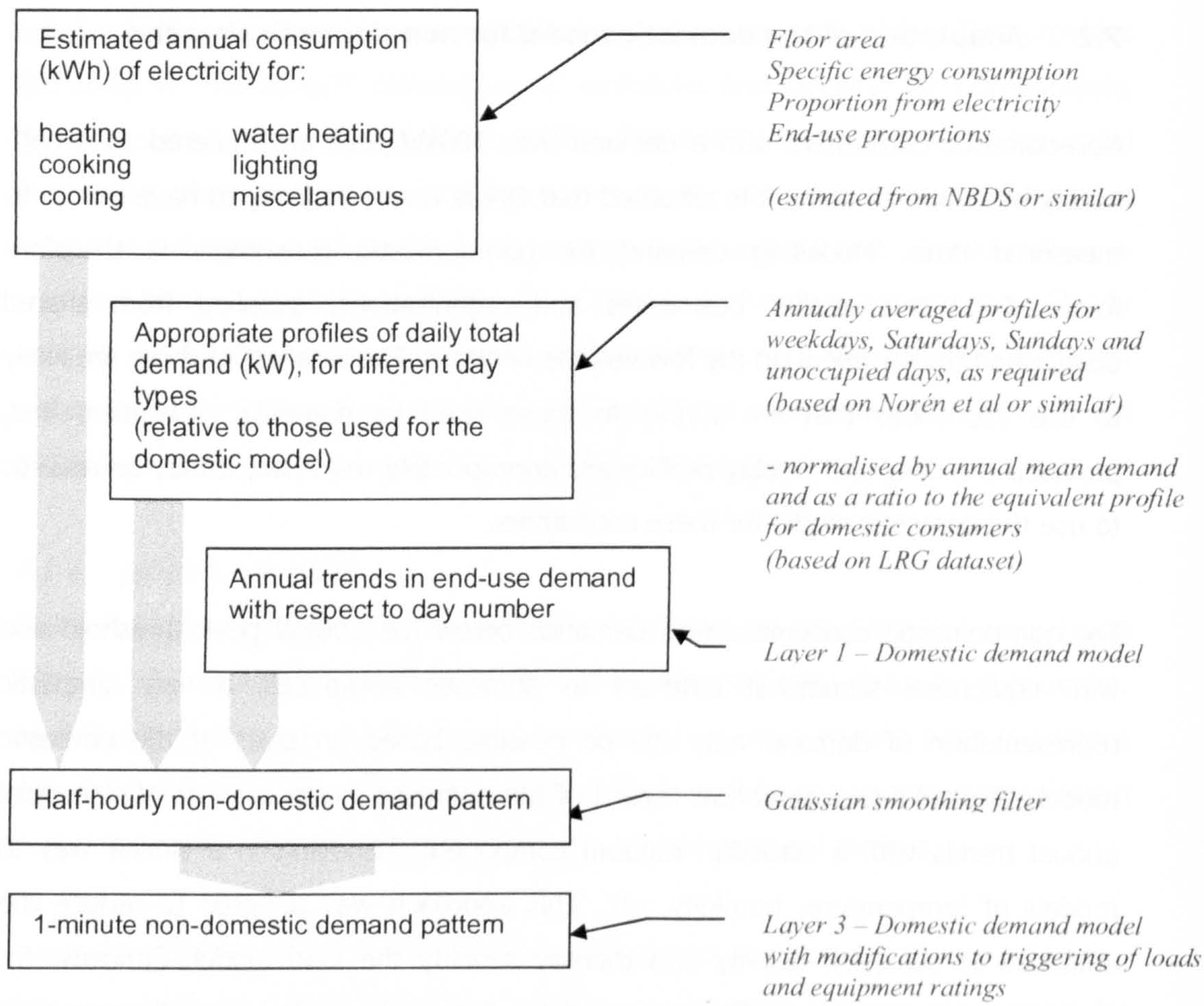


Figure 7-2: Conceptual representation of the basis for a non-domestic demand model, based on elements of the domestic model

The various steps of this adaptation of the domestic model are perhaps best illustrated by example and the next section describes the case for estimating electricity demand in schools.

7.3 Example of estimating non-domestic demand: schools

7.3.1 Estimates of annual end-use consumption - schools

The detailed categorisation of schools in the NBDS covers four types of school (state primary and secondary, special and private). Floor area estimates for each category can be selected randomly from within a defined range, using a Gaussian distribution ([Bruhns et al, 2000], values provided in Appendix F, section F-4). Alternatively, using a mean ratio for plan roof area to gross floor area of 0.41, derived from the

NBDS sample, the floor area can be estimated from a GIS plan view. For this example, a secondary school with a floor area of 6721 m^2 is chosen (half-hourly data were made available from other research for such a school).

The specific annual energy consumption for schools as a group is also assumed to have a Gaussian distribution, with a mean and standard deviation of 224 and 176 kWh/m^2/annum [Elsayed et al, 2002]. In the schools surveyed by the NBDS 34% of energy was supplied by electricity [Pout, 2000]. For this example, the measured data provides an annual electricity consumption of 329 MWh. However, this is the only input value required in the proposed non-domestic model and could be estimated randomly if data were not available.

The estimated proportions (based on [Pout, 2000]) of electricity used in schools by end-use, again based on the NBDS samples, are:

Heating	0.14
Lighting	0.43
Water heating	0.05
Cooking	0.14
Cooling	0.05
Miscellaneous	0.12

To simplify the model, cooking includes any catering equipment and miscellaneous demand includes computing and small power equipment (if required, the user can zero these contributions since many urban schools will probably use gas for heating and some may not have catering facilities). In the absence of specific information, random assignments can be made on the basis of probability (e.g. 7% of UK schools use electricity for heating [Elsayed et al, 2002]). For our particular example, it is assumed that the school does not use electricity for space heating. Used together, these estimates provide the annual consumption (kWh) for each of the six end-uses.

7.3.2 Estimates of daily demand profiles - schools

The electricity demand in schools depends very much on whether the building is occupied or not. As well as bank holidays and weekends, the school holidays must be taken into account. Estimates of dates for holidays, which the user may override with specific local information, are an essential feature of demand modelling. Different daily load profiles are therefore required for days when the school is likely to be occupied and those when the school is closed. Variations in such patterns might have to be more sophisticated if the school building were used for multiple purposes. For our example, the school is assumed to adopt a typical pattern of occupancy (either occupied, during weekdays, or unoccupied, during public/school holidays and weekends) and with holiday periods that are normal for central England.

Layer 1 of the domestic model is used to generate an annual pattern of total demand. Two daily profiles for a typical domestic consumer are derived from these demands by calculating annual averages for those days designated as occupied and unoccupied (these profiles are normalised by the mean demand for the entire year). The study of Swedish schools [Norén, 1997] can be used as a basis to provide similar annually averaged daily profiles (normalised by the annual mean) for schools. These two sets of profiles can be compared and a ratio of the school demand to the domestic demand calculated in each half-hour (Figure 7-3).

There is likely to be far more activity in schools during the daytime compared to the typical domestic situation and also comparatively higher demands occur in the early hours of the day, when control systems may still operate and security lighting remains on. Demand after the school day ends is likely to be relatively low. Thus, on occupied days, the comparative ratio of the school profile is above unity until about 16:30. On unoccupied days, the school demand is likely to be relatively constant throughout the day and the scaling factor is above unity to around 06:00 in order to adjust the domestic daily profile appropriately.

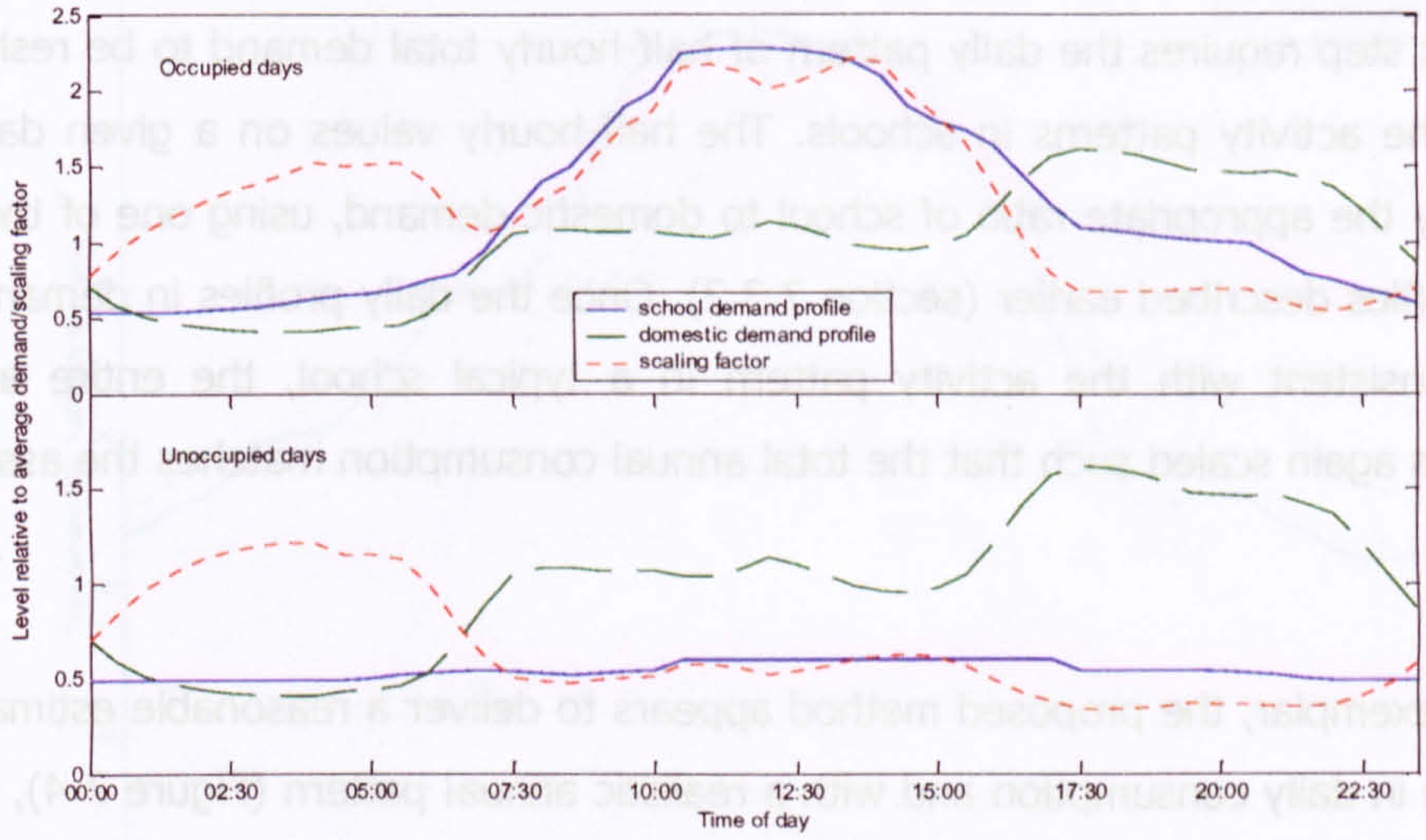


Figure 7-3: Relative daily demand profiles for domestic consumers and schools, with the scaling factor (school demand/domestic demand) for occupied and unoccupied days

If it is assumed that the relationship between schools and domestic consumers over the day remains relatively constant throughout the year, these ratios may be used to reshape the pattern of half-hourly demand from layer 1 (explained further in section 7.3.4).

7.3.3 Annual trends in end-use demand –schools

Assuming the annual trends of the half-hourly demand for domestic consumers can be considered to be largely independent of activity and dependent on ambient conditions, then the annual pattern of end-use demand from layer 1 of the domestic model can also be used for schools (this assumption will be explored later). Layer 1 is used to calculate end-use patterns for space and water heating, lighting, cooking, refrigeration and miscellaneous demand.

The annual trends in each end-use and for each half hour, are based on the sinusoidal relationships with day number. The entire trend is scaled such that the annual consumption matches the assigned value (derived using the process from section 7.3.1). The patterns in end-use demand are summed to provide the total (active) demand. This gives an approximation of the way in which the different end-use components contribute at different times of the day, week and year.

7.3.4 Half-hourly demand – schools

The next step requires the daily pattern of half-hourly total demand to be reshaped to suit the activity patterns in schools. The half-hourly values on a given day are scaled by the appropriate ratio of school to domestic demand, using one of the two daily profiles described earlier (section 7.3.2). Once the daily profiles in demand are more consistent with the activity pattern in a typical school, the entire annual pattern is again scaled such that the total annual consumption matches the assigned value.

For our exemplar, the proposed method appears to deliver a reasonable estimate of the scale in daily consumption and with a realistic annual pattern (Figure 7-4), given differences between the assumed and actual dates of school holidays. There is clearly more variation from day to day in the measured data and the comparison illustrates some of the over-simplifications that arise from using the basis just described. However, to generate this demand pattern required only one user input (total annual electricity consumption).

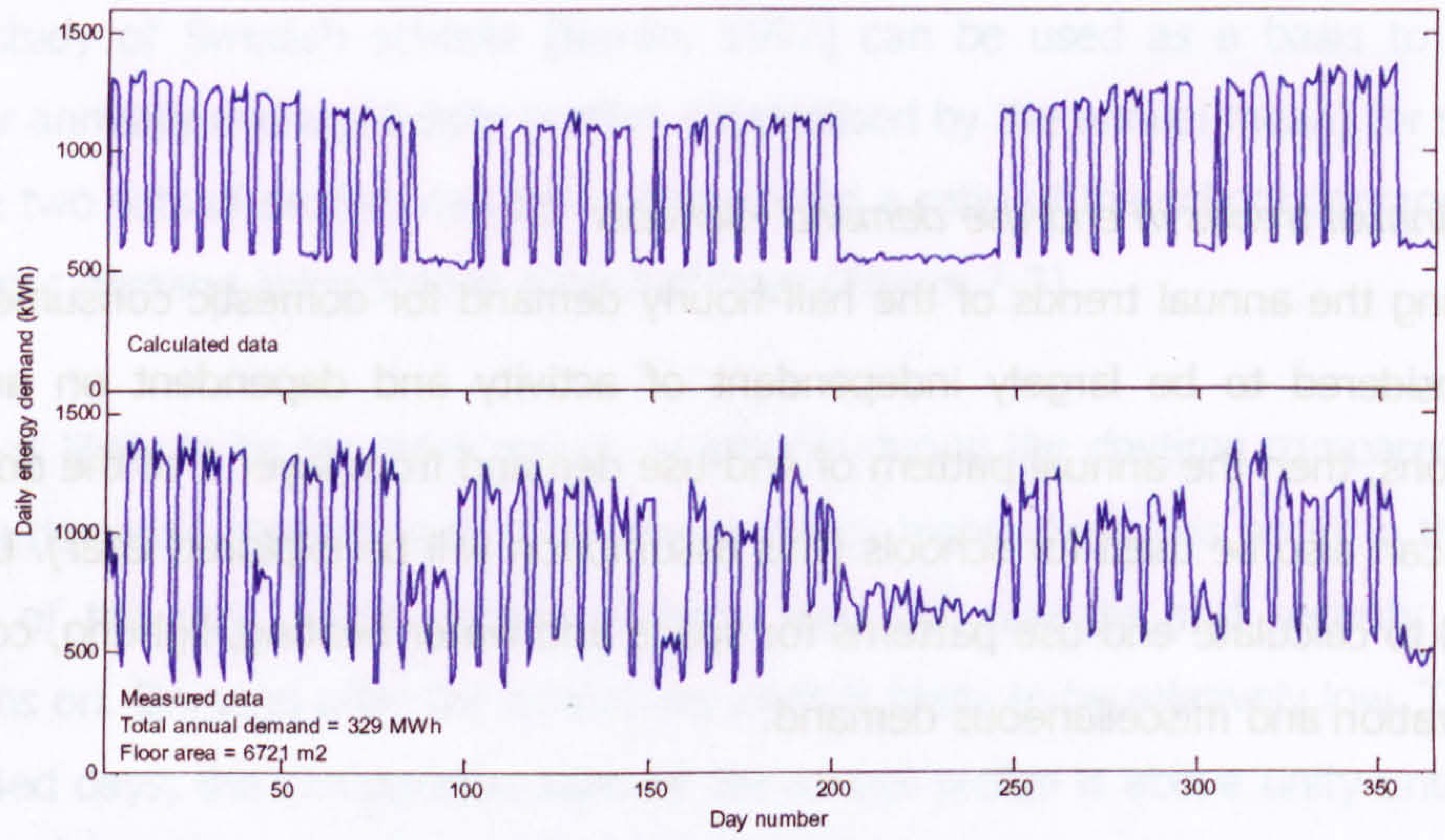


Figure 7-4: Comparison of daily energy demand estimated by the school sub-model and that measured for a medium sized secondary school

Averaged over a complete year, the reshaping of the domestic data using the profile for Swedish schools also appears to give a realistic comparison (Figure 7-5).

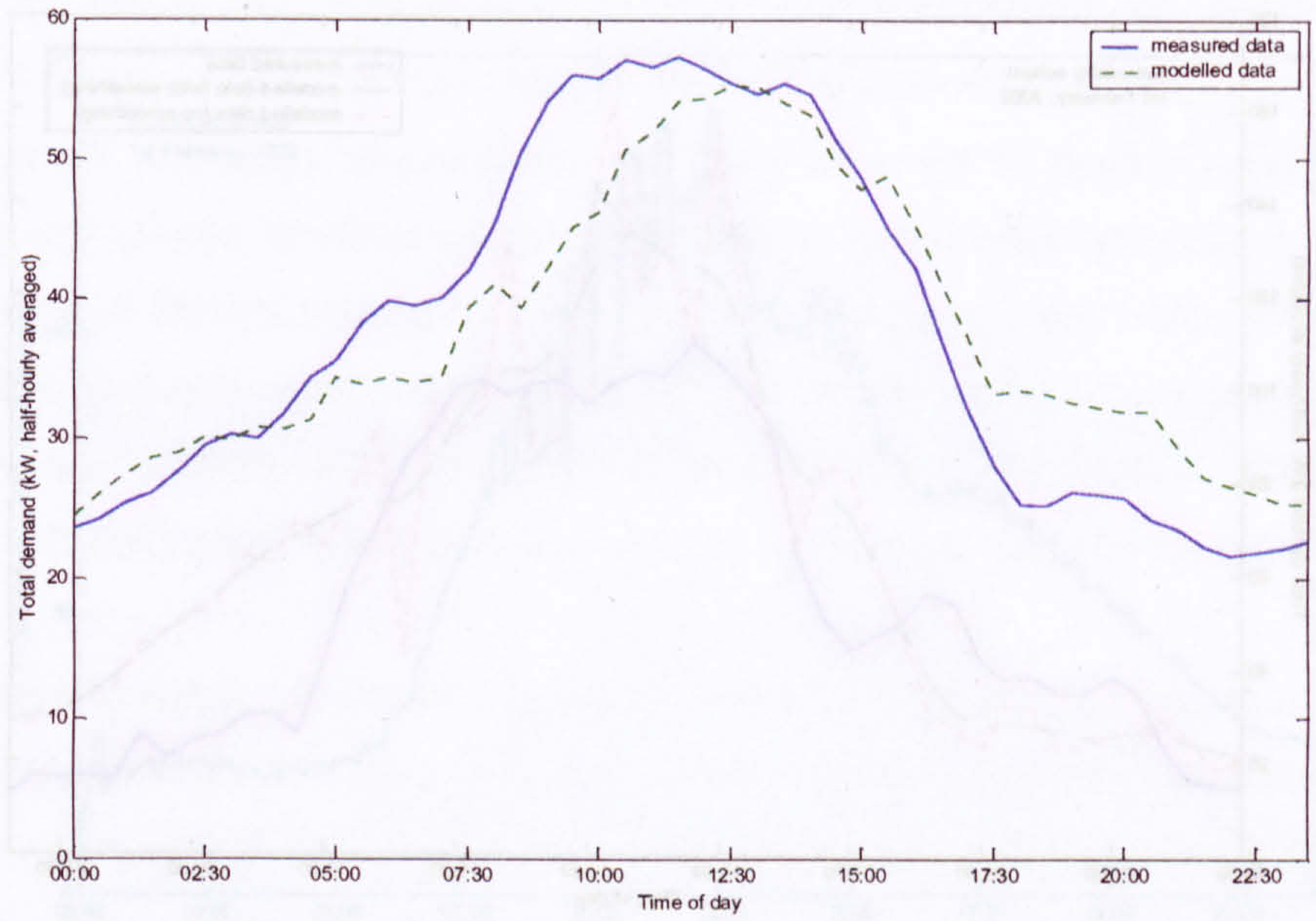


Figure 7-5: Comparison of the averaged daily demand profile estimated by the school demand model and that measured for a medium sized secondary school

However, when examined in more detail, for individual days, the modelled demand is shown to vary significantly from one half-hour to the next (Figure 7-6). This variation arises from the random components applied to the demand in layer 1 of the domestic model. The distribution of the random components was derived from the LRG domestic data and when scaled to match the far higher annual consumption for a school, the random variation is similarly scaled upwards. Such sudden steps in demand are unrealistic when compared to measured demands and this represents one of the weaknesses of the technique described. A smoothing filter (based on a Gaussian kernel [Brett, 1999]) can be applied to improve the comparison.

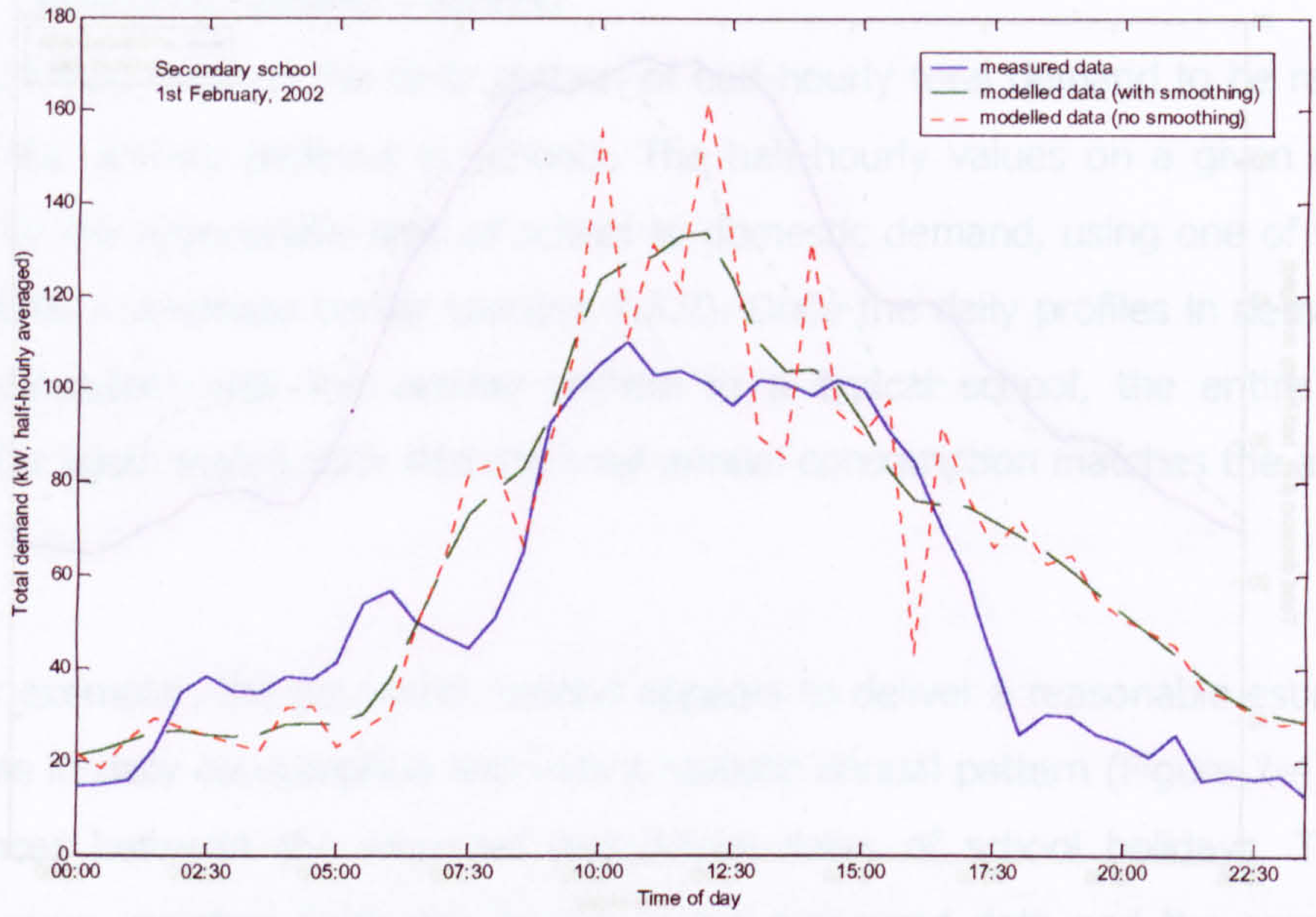


Figure 7-6: Comparison of measured and calculated demands for a secondary school (1st February, 2002), showing the effects of adding smoothing

7.3.5 1-minute demands – schools

To create 1-minute averaged demands from half-hourly values for non-domestic consumers represents a very difficult challenge. If the electrical equipment used is similar to domestic appliances then the method adopted (using assigned demand as a probability for triggering events) in layer 3 of the domestic model, is still reasonable. This approach could also be used given some knowledge of more realistic equipment ratings and use patterns for particular categories of non-domestic consumers. Alternative values could then be slotted into layer 3 and events triggered in a similar way to the domestic model. No 1-minute data were available on which to base this kind of development and no other studies, similar to that of Mansouri et al for domestic appliance use, could be found.

For the purposes of this example, the 1-minute demands for cooking, refrigeration and water heating are assumed to be at a constant level throughout each half-hourly period whilst lighting and miscellaneous events are triggered in a similar way to domestic demands, assuming they occur through use of multiple small devices. Whether or not these assumptions give rise to a realistic level of 1-minute demands (Figure 7-7) is unknown.

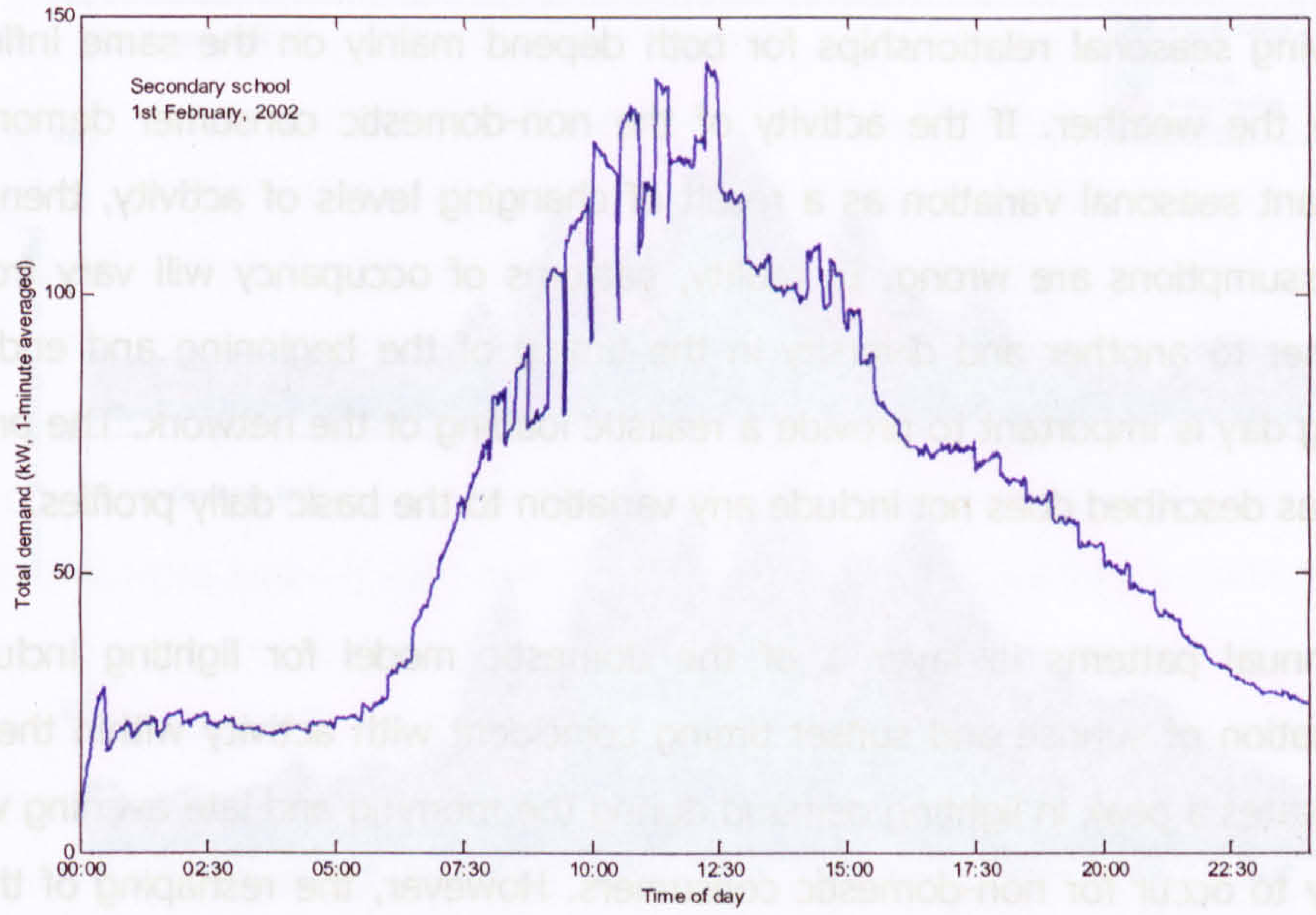


Figure 7-7: Calculated 1-minute averaged demands for a secondary school (1st February, 2002)

Clearly if this representation of the apparent demand were at all realistic, it would be possible to assign a power factor to each end-use to derive some estimate of the reactive load.

7.4 Limitations of the approach for non-domestic consumers

Assuming the user is able to determine whether or not a connection node refers to a non-domestic consumer and is able to categorise the activity (both of which can represent a significant challenge) the next stages in estimating a realistic network loading require either specific knowledge or gross estimates. Even within a given category of activity, there will be a considerable degree of approximation if random values are selected for floor areas, specific energy consumption values, proportionate use of electricity and end-use assignments. Using the NBDS and NDEEM research provide typical values but wide variations occur in practice.

Using a limited range of daily profiles (annual averages) assumes that the comparison between the daily activities of a non-domestic consumer will remain constant over the year in relation to a domestic consumer. This is only true if the underlying seasonal relationships for both depend mainly on the same influences, notably the weather. If the activity of the non-domestic consumer demonstrates significant seasonal variation as a result of changing levels of activity, then clearly such assumptions are wrong. In reality, patterns of occupancy will vary from one consumer to another and diversity in the timing of the beginning and end of the working day is important to provide a realistic loading of the network. The proposed model as described does not include any variation to the basic daily profiles.

The annual patterns in layer 1 of the domestic model for lighting include the combination of sunrise and sunset timing coincident with activity within the home. This creates a peak in lighting demand during the morning and late evening which is unlikely to occur for non-domestic consumers. However, the reshaping of the daily profile for non-domestic consumers is generally such that the total demand is scaled heavily downwards at times that coincide with peaks in domestic activity and hence also in lighting demand. As such the effect of adopting the domestic annual patterns for non-domestic lighting demand is less of a problem than it might at first appear. The contribution of lighting demand to the total will tend to be over-estimated in the morning and late evening, especially in the winter (Figure 7-8). This could affect the estimates of power factor and reactive load to some extent (lighting is associated with a purely resistive demand, with a power factor of 1.0; the estimates made by the model could over-estimate the power factor value for the morning and late evening) although the total active demand (which is adjusted in scale and profile after the end-use components have been added together) will not be affected.

Cooling demands, in the proposed model for the non-domestic consumers, are associated with domestic refrigeration which may be realistic for situations where appliances are similar. However if demand is for space cooling, the load will in practice be split between refrigeration and a more constant requirement from fans. Solar warming has an impact on refrigeration for air conditioning especially since the units are frequently placed on exposed roofs [Wright, 2004]. As such the phasing of demand, viewed as an annual trend, will be different to that for refrigeration units operating inside buildings, as for domestic appliances.

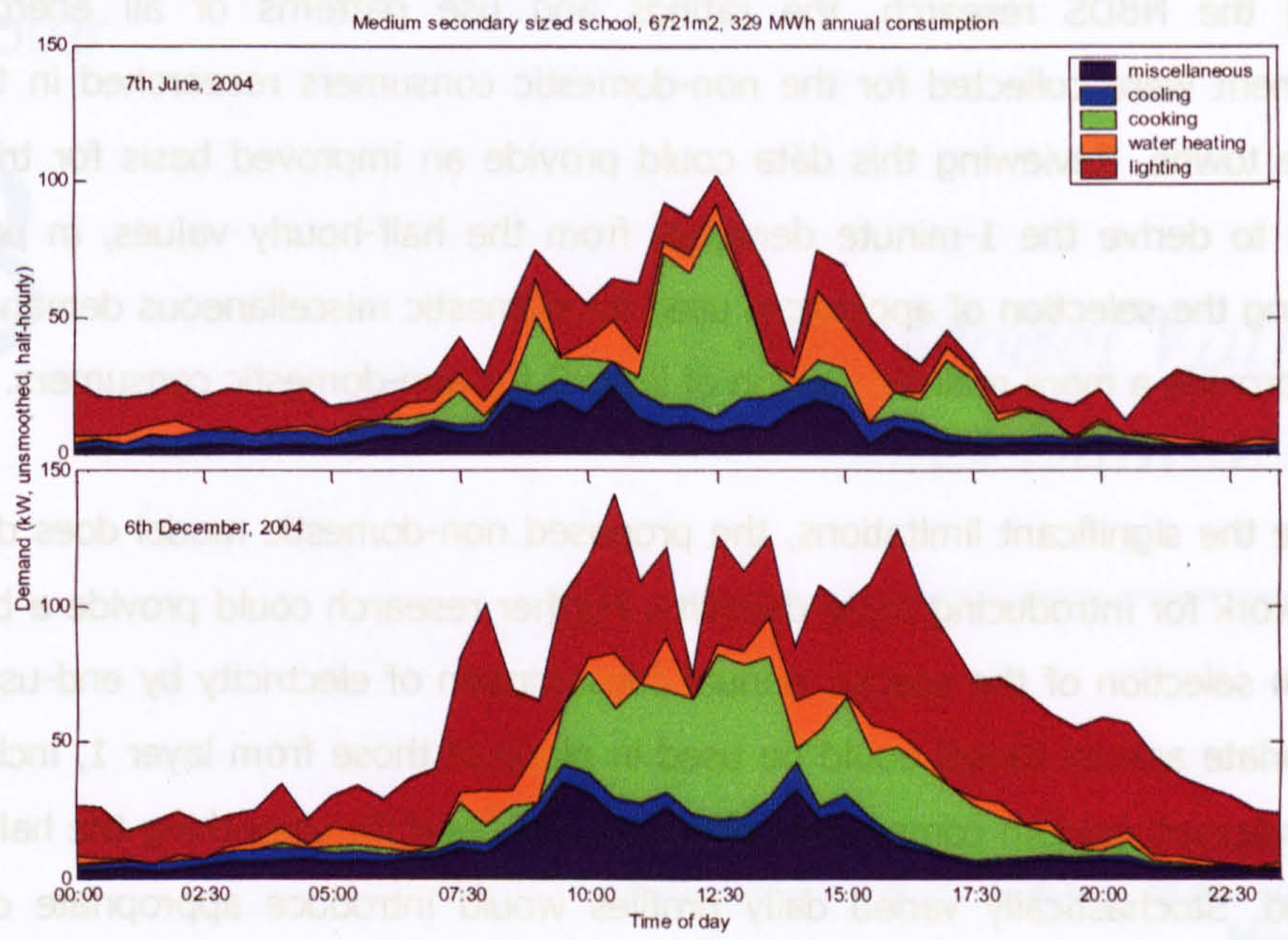


Figure 7-8: Modelled half-hourly demand (unsmoothed) by end-use for a secondary school on two days (7th June and 6th December, 2004)

Finally, the limitations associated with deriving the 1-minute demands for non-domestic consumers have already been highlighted. Whilst assuming a relatively constant demand during a given half-hour may be realistic for some consumers during the working day (e.g. schools, shops, offices), for others, notably with considerable variation in process demands (e.g. welders, platers), such assumptions will be unreasonable.

7.5 Extensions to the proposed non-domestic model

The proposed non-domestic model has been developed for many different categories of non-domestic consumers (including shops, offices, hotels and schools) for which the relevant parameter values appear in Appendix F. If datasets of averaged half-hourly demand were available, as provided by the LRG's for domestic consumers, then the annual patterns could be improved. Establishing profiles similar to Norén's for the UK would also provide improvements in the reshaping of the daily profiles and could provide a statistical basis on which to vary the leading and falling edges of the demand at the start and end of the working day.

During the NBDS research, the ratings and use patterns of all energy-using equipment were collected for the non-domestic consumers researched in the four sample towns. Reviewing this data could provide an improved basis for triggering events to derive the 1-minute demands from the half-hourly values, in particular replacing the selection of appliances used for domestic miscellaneous demands. This could provide a more realistic version of layer 3 for non-domestic consumers.

Despite the significant limitations, the proposed non-domestic model does deliver a framework for introducing more diversity. Further research could provide a basis for random selection of the specific annual consumption of electricity by end-use. More appropriate annual trends could be used in place of those from layer 1, including a more relevant random component, removing the need for smoothing the half-hourly demand. Stochastically varied daily profiles would introduce appropriate diversity even within a single category. Equipment ratings could be varied for triggering 1-minute averaged demand events and more appropriate duty cycles.

7.6 Summary: Chapter 7

Representing non-domestic demand represents a very significant challenge since the diversity in activities, patterns of demand and equipment used is far greater than for domestic consumers. A method has been described that adjusts the daily profile of a domestic consumer to suit that of a given category of non-domestic consumer by scaling the annual trends of the end-use demands. The relative contributions and total demands are scaled to match assigned values of specific annual consumption which are derived from the NBDS research. Whilst the method clearly has several limitations, the proposed model could provide a framework for future development.

The non-domestic model as described has been shown to give a relatively realistic representation of demand for a medium sized secondary school, given that only one value – the annual electricity consumption – was required as the user input. In the next chapter, applications of this non-domestic model to other schools, a shop, office and hotel are described and compared against measured data as part of a wider validation exercise.

Chapter

8

Load Model Validity and Limitations

I'm no model, lady...
A model's just an imitation of the real thing
Mae West

This chapter discusses the extent to which the load models provide an adequate representation of the electricity demand in the context of a typical urban LV network. To provide a basis for this discussion, the domestic model and the approach for non-domestic consumers were tested against measured demands. No data were specifically gathered within the Solar City project for this purpose (only the half-hourly aggregated demand on a single feeder of a primary transformer, were available). However, datasets have been provided by other researchers although, as described later, these all have their limitations. Two relate to domestic samples, one of which includes homes of very similar description that are far from typical, the other relates to a study for which no detailed information of the homes exists. Further comparisons are also made for two schools and a large office block, although this is only possible at the half-hourly demand level.

Obtaining reliable data for demand, domestic or non-domestic, is notoriously difficult and it is this vacuum that these load models endeavour partially to fill. The models were never intended to provide accurate predictions of the electrical demand at a specific connection point but rather to give a realistic set of data to load an urban LV network. Whilst the available data does not permit a completely satisfactory comparison within this context, it is included to provide further assessment of the models and to highlight the considerable difficulties involved in examining demand data. Various techniques are required to demonstrate whether the models provide a realistic scale, pattern and diversity of demand. The first part of the chapter briefly explains these methods and in the sections that follow, analyses of the comparisons are presented. Exercising the models has provided information about their operational performance and some of the practical aspects are described. Finally, drawing on the results of the comparisons, some limitations are identified.

8.1 Methods of comparing demand data

8.1.1 Total consumption

The total energy consumption (in kWh) is simply calculated as a sum of the energy demands over a given period. This figure is frequently used on a national basis for annual consumptions, to derive the associated emissions, to establish basic trends in demand and to assess the broad effects of demand reduction strategies. In terms of the model, for an individual consumer total consumption tests the assumptions made about demand allocation. For a group of homes, it also tests diversity. In both cases, it verifies the overall scale of demand.

8.1.2 Peak/Average Demands

Estimates of the peak annual demand are frequently used to size network equipment. The relationship between the average and peak values provides the load factor, also used in network design. Peak and mean values depend on the time period over which the demand is averaged. Looking at peak and average demands tests the model in terms of the scale of demand predicted and, at a basic level, the pattern of demand.

The total demand for a group of consumers is the diversified demand. The peak demand for the group (the maximum diversified demand) is an important factor for sizing transformers. Summing the maximum demands per consumer and comparing this to the maximum diversified demand provides a diversity factor. Comparing values from measured and modelled data tests the diversity between consumers.

8.1.3 Profiles

Profiles are usually generated on a daily basis. They may be averaged profiles over a year, season (for different days or tariffs) or for specific days. Comparison of the modelled versus measured profiles confirms the overall correctness of the patterns in the demand - averaged profiles tend to show basic trends whilst those on individual days (e.g. the four equinox days) provides more detailed trends, revealing underlying reasons for any divergence between actual and modelled demands.

Comparison of profiles for an individual consumer can establish how appropriate the models might be for use on a per building basis whilst profiles for groups validate the general pattern of demand and the degree of diversity. Those for a single day provide an indication of whether the model represents the spiky characteristics of the load, arising from individual appliances. Comparison of group averages and ranges of maximum and minimum demand for the daily profiles should provide further evidence of the reliability of modelled diversity.

8.1.4 Cumulative density function

The cumulative density function provides a picture of the probability that the demand will not exceed a given value. This function for the total demand of a group of domestic consumers has generally been found to follow a gamma distribution function [McQueen, 2002]. It can be used over various time spans (annual, seasonal, etc.) and for different time intervals for demand averaging. It provides an indication not only of the scale but also the distribution of demand levels. Cumulative density functions are used for LV network voltage drops to obtain some statistical understanding of risk with regard to the power quality. For the purposes of validating the load models, cumulative density functions are presented for the finest time interval possible and for the complete span of the dataset.

8.2 Comparison for domestic dataset (1)

8.2.1 Description of domestic data (1)

Whilst investigating the performance of PV panels [Firth et al, 2003], electricity demands were measured for a community of housing association homes in Leicester. All were semi-detached bungalows with identical floor areas and mostly occupied by single elderly people, representing a group relatively far from the typical home and with potentially very low diversity. Interviews with the residents provided a list of the main appliances (although not the specific ratings) owned in 17 of the homes. The measurements were taken on a 5-minute averaged basis with data from 1st July 2002 to 31st June 2003 selected to provide a comparison over a complete year. The domestic load model was used to generate 1-minute averaged demands for each house, based on the known appliance ownership, and were aggregated to 5-minute averaged demands for comparison.

For the test case, the measured demand data are calculated from the sum of the PV export and the net imported demand. These quantities are measured using two separate systems. A slight mismatch in the timing of the systems means that for certain homes on some days there appears to be a negative demand. This aspect of the dataset has been ignored (negative values are set to zero).

8.2.2 Total demands

The group measured annual energy consumption (the sum of 5-minute averaged data) was 41,888 kWh compared to a modelled value of 41,668 kWh – a difference of 0.5%. This is well within the errors that are typically accepted for energy modelling (for example, the DREAM model estimated domestic annual consumption over an area of Leicester within 2-6% [EERU, 2004]; electrical meters operate on a +2.5% to -3.5% error basis for load values [Elexon, 2004(b)]). For individual consumers, the range of measured consumption was from 990 to 4676 kWh (one of the homes was occupied by a family of four) compared to a modelled range of 1845 to 4420 kWh.

The over-estimates in the total consumption for some individual homes appear to arise mainly from assumptions about the miscellaneous demand. For several of the homes in the test case, very few appliances have been assigned and the miscellaneous demand accounts for a large proportion of the modelled total. For example in one home (Figure 8-1), the daily energy consumption for the 21st March is modelled at 6.8 kWh compared to a measured value of just 2.9 kWh (a typical minimum daily demand per house is 7.2 kWh [Newborough & Augood, 1999]). The house has only four appliances assigned – a refrigerator, hob, oven and an electric kettle. Miscellaneous demand provides 48% of the modelled total energy usage. In this example, the level of the residual demand at around 100W is realistic but the measured data show a far more intermittent use pattern. Such errors are likely to be less significant for more typical homes, with more appliances and with a greater likelihood of a constant stand-by demand.

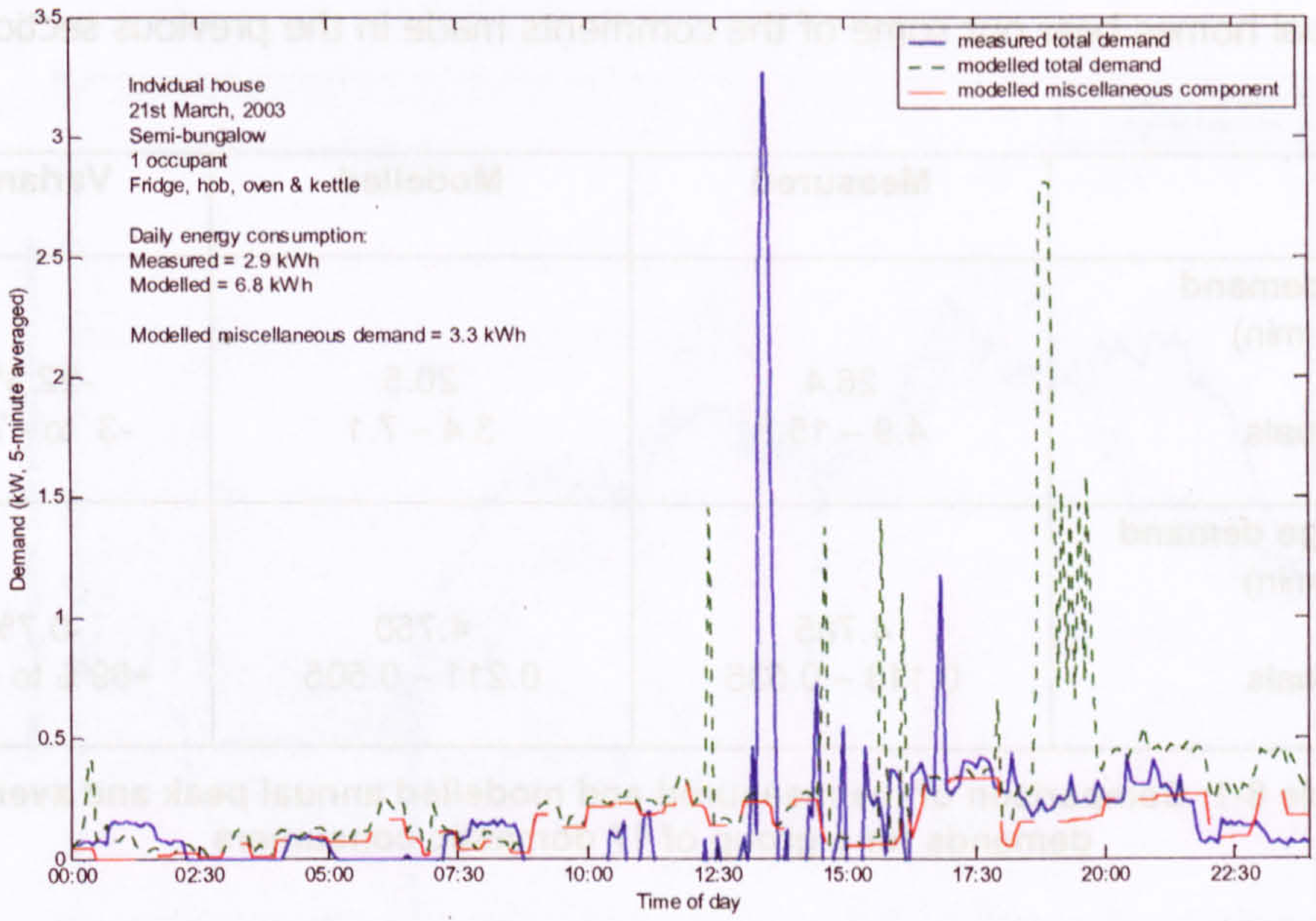


Figure 8-1: Comparison of the measured and modelled demands for a single house from the domestic dataset (1), showing the relative contribution of the miscellaneous demand[1]

For other homes, the under-estimates in energy consumption are thought to arise from the use of electric showers (all bungalows are fitted with 8kW showers, used instead of baths), which the load models do not specifically represent. Closer analysis of the measured data also suggests use of portable electric heaters (peak rating around 3kW) which in the model are included as one of a possible 20 randomly selected appliances for the miscellaneous demand.

[1] In this particular example, the measured data show a negative demand of as much as 0.54 kW due to errors in the calculations from different metering systems. Such errors tend to occur sporadically during periods of PV export. However, small errors in the data for this particular test case can have some considerable impact on the comparisons with the modelled data because the overall levels of demand are generally extremely low when compared to national averages.

8.2.3 Peak/Average demands

The comparison of the measured and modelled peak and average demands (for a complete year, table 8.1) suggest that the model tends to under-estimate the peaks in demand although the group-average value is realistic. The comparisons for individual homes bear out some of the comments made in the previous section.

	Measured	Modelled	Variance
Peak demand (kW, 5 min) Group Individuals	 26.4 4.9 – 15.8	 20.5 3.4 – 7.1	 -22.3% -3 to - 71%
Average demand (kW, 5min) Group Individuals	 4.785 0.113 – 0.535	 4.750 0.211 – 0.505	 -0.7% +89% to -44%

Table 8-1: Comparison of the measured and modelled annual peak and average demands for a group of 17 domestic consumers

The annual load factor for the group is 18% compared to 23% for the modelled data. Annual load factors for individual homes lie between 2.2 and 3.4 %. The model estimates a range of 3.6 to 5.2%, arising from a tendency to under-estimate the annual peaks in demand. Although significant peaks were observed in the 1-minute data, when averaged on a 5-minute basis, the modelled demand tends to be less spiky than the measured. This is again thought to be related to the use of showers in the test case homes, where high levels of demand may be sustained over several minutes. The model tends to create shorter bursts of high demand and could potentially be improved by developing a separate module for showers.

The diversity factor (in this case defined as the sum of the annual peak demands of the consumers to the diversified group peak demand) is 4.9 for the measured data and 3.7 for the modelled data. Once again this suggests that the model tends to over-estimate the diversity in the peak demand and under-estimate the peak value within this particular community of homes although the averaged demands appear realistic.

8.2.4 Daily Profiles

Considering first the aggregated demands for all the houses as a group, the daily profile, averaged annually, compares relatively well in terms of scale (Figure 8-2).

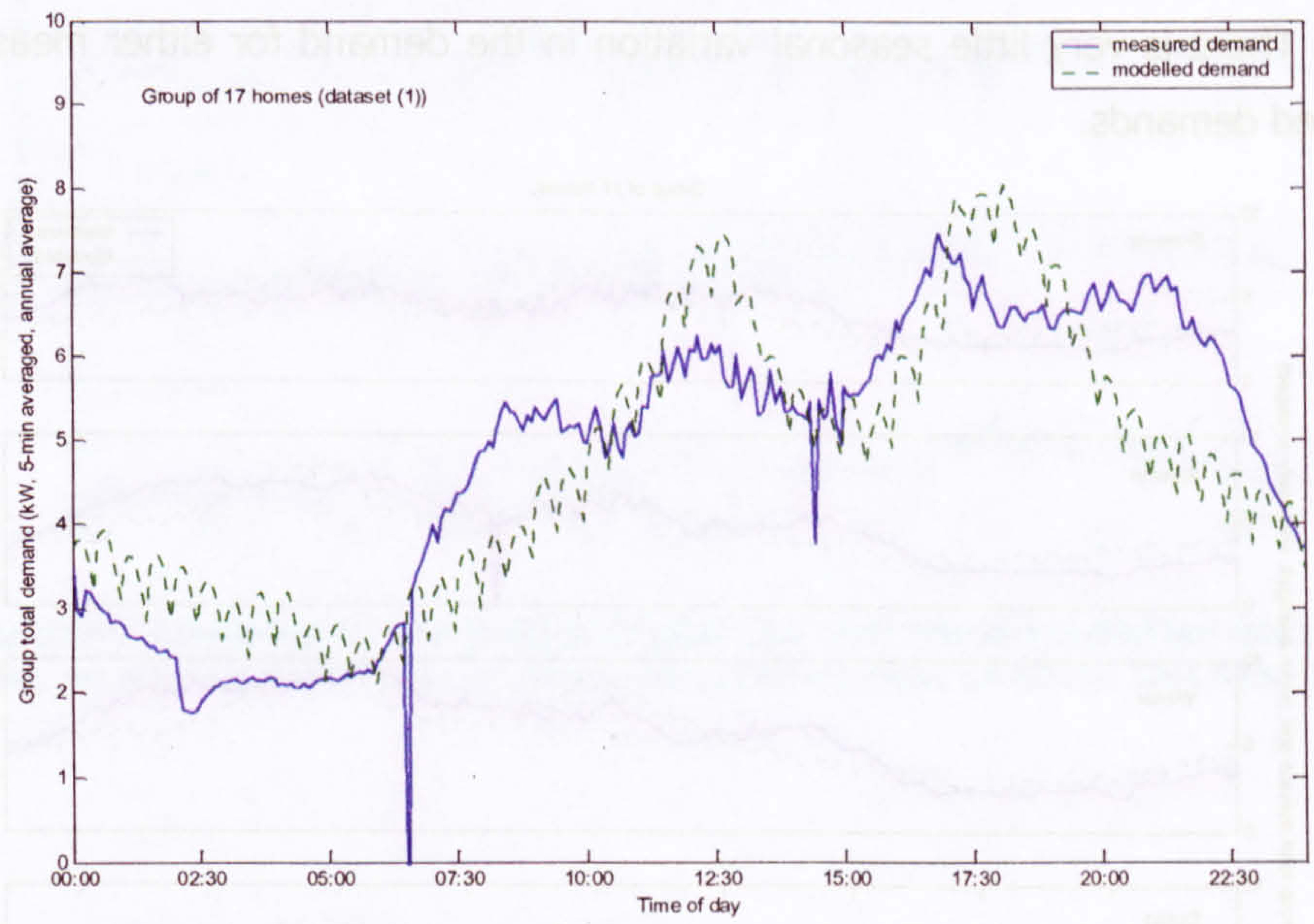


Figure 8-2: Comparison of measured and modelled annual averaged daily profile for the aggregated demand of all the test case homes for dataset (1)

The dips in the measured demand around 07:00 and 14:30 illustrate the problems with the dataset mentioned previously. The model fails to capture the peaks around 08:00 and 21:00, which occur in around 60% of the homes. This is probably due to an under-estimate of the lighting demand, which is heavily scaled down in the model as a result of adjustments for single occupancy and ACORN rating F, applied for most of the dwellings (section 5.7). The modelled profile also tends to over-estimate the peaks around midday and 18:00 which most likely arise from an over-estimate of cooking activity (since kettles, cookers and microwaves all share the same basic pattern of use in layer 1). The 'ringing' in the calculated demand is a result of the algorithms used to model refrigeration appliances (section 6.2). In this test case, refrigeration represents a significant proportion of the demand and the profiles of total demand, especially for homes owning appliances with freezing capacity, are much influenced by the switching in and out of cold appliances every half-hour. The assignments in the model of cooling demand and appliance ratings are also very similar across the group since the dwellings are so homogeneous. Such problems are less likely to arise for a more diverse group as might be connected to an LV network. In general, the shape of the profile and scale of demand compare well.

On the basis of seasonal averages, the comparisons remain similar (Figure 8-3), suggesting that the underlying annual patterns provide a satisfactory basis for the model. There is very little seasonal variation in the demand for either measured or modelled demands.

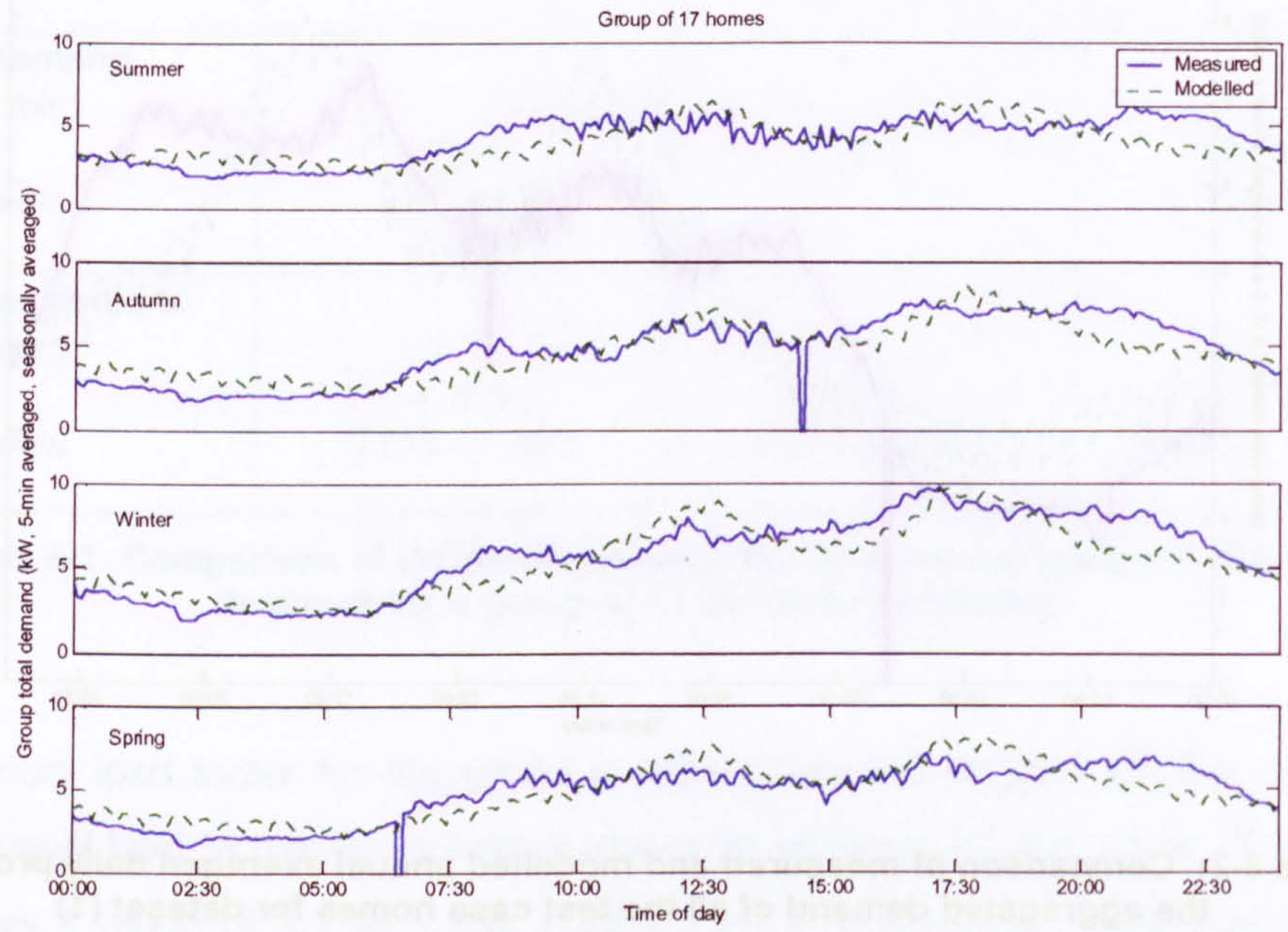


Figure 8-3: Comparison of measured and modelled seasonally averaged daily profile for the aggregated demand of all the test case homes

By comparing the modelled data against the test case for individual days, it should be possible to identify whether the peak levels are consistent (Figure 8-4). The test data appears more spiky than expected during the middle of the day (this occurs more when the PV arrays are showing a significant output and it is possible that the test data are affected by negative 'drop-outs'; it is very unlikely that for a group of 17 homes, the group total demand will be zero). The comparison in mid-winter and mid-summer shows that the model works well at these times of the year but tends to smooth the demand slightly during spring and autumn days, which are subject to more changeable weather. Again, the scale and overall pattern of demand during the day appear to be adequately represented by the modelled values.

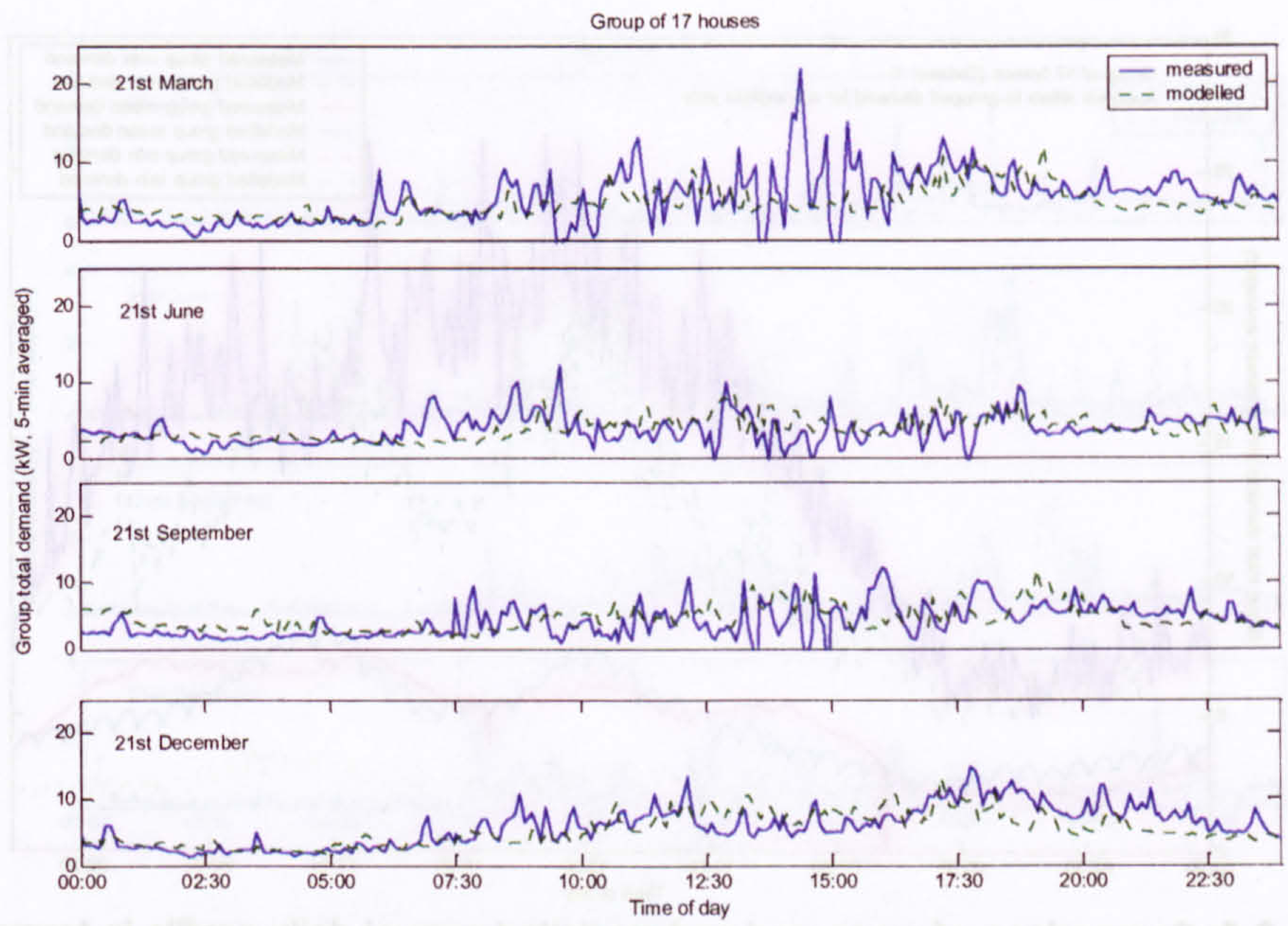


Figure 8-4: Comparison of measured (solid line) and modelled (dotted line) daily profiles on four specific days for the aggregated demand of all the test case homes

Whilst the model captures the group averaged daily demand (for the year) reasonably well, it does not capture the full extent of the peak demand (Figure 8-5), representing the maximum of the group demand over the whole year. This comparison suggests that the diversity is over-estimated and peaks in demand under-estimated when activity is likely to be high. At other times of the day, the model performs relatively well in terms of both average and peak demands. This variation is thought to arise from the down-scaling of lighting demand due to occupancy and lifestyle factor, and because the model does not fully capture the demands from showers and portable heaters, especially for 5-minute averages. It may also indicate that the sample group behave in a less diverse way than might be expected.

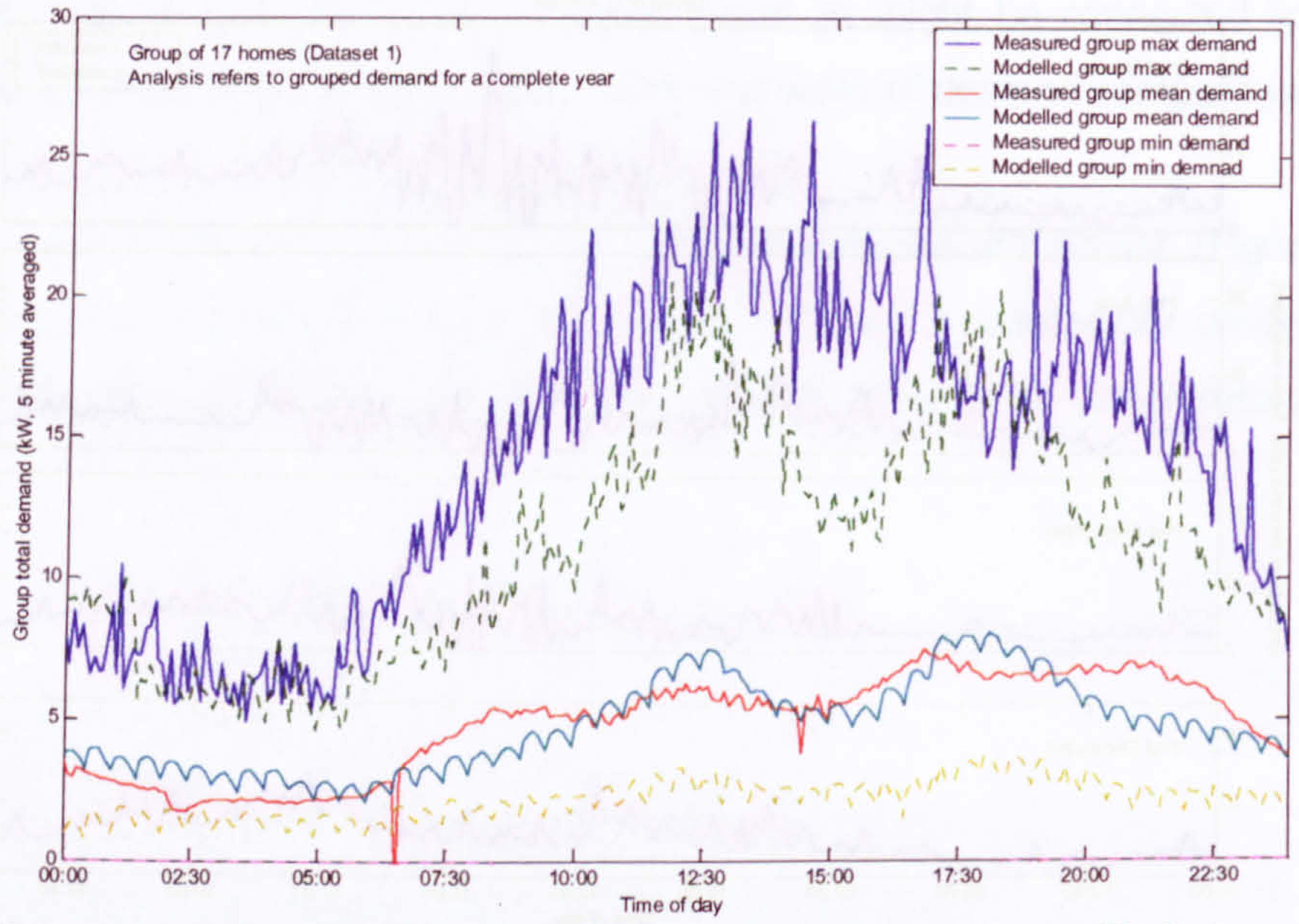


Figure 8-5: Comparison of measured and modelled annual daily profile in terms of the average group demand per house and the peak demand for the group of houses

Looking at the group demand presents only one part of the story, since the inherent averaging tends to smooth the profiles. The measured and modelled demands for two houses for four individual days (the equinoxes) are compared (Figure 8-6). In broad terms, the scale and frequency of events appear similar.

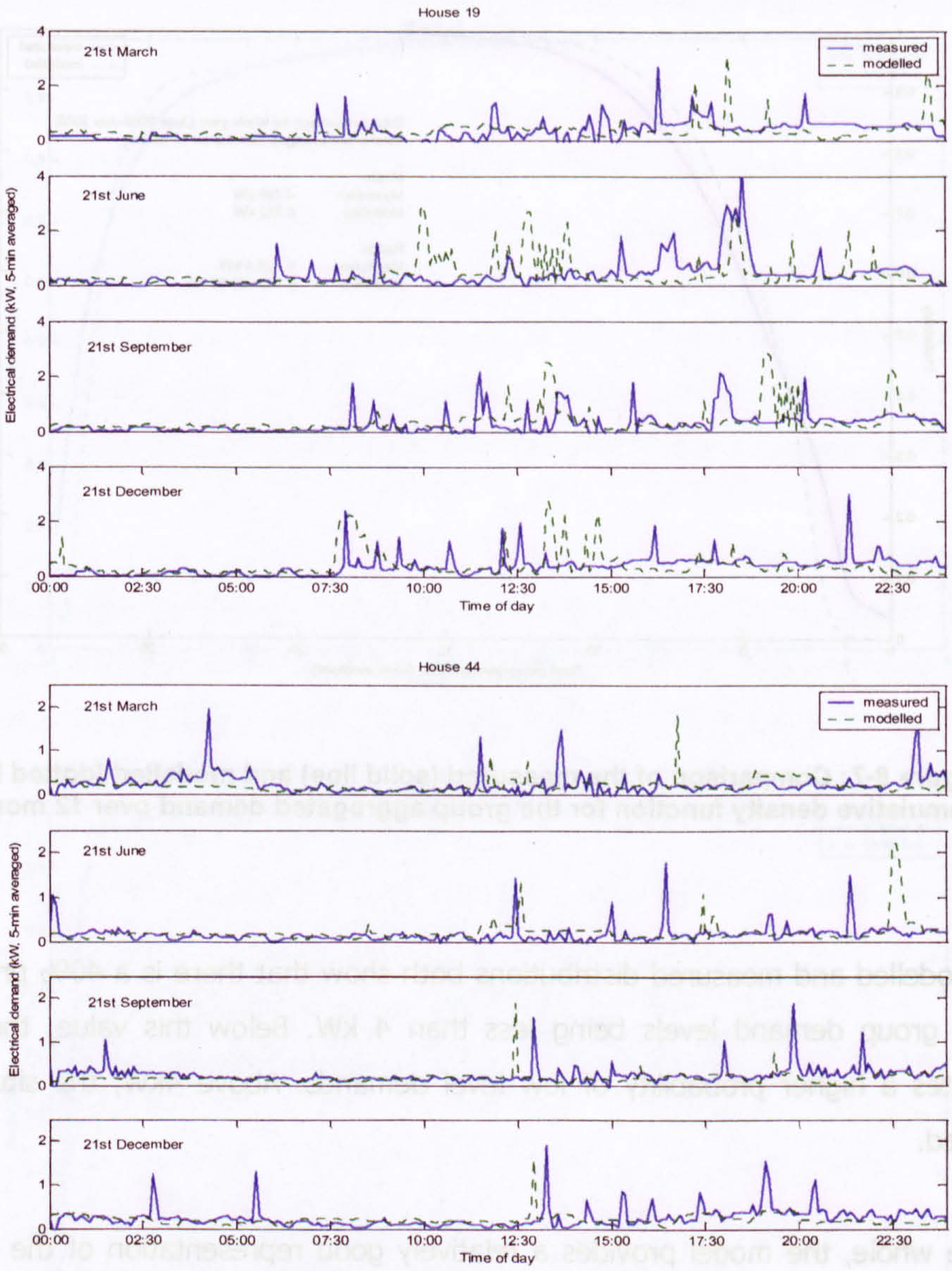


Figure 8- 6: Comparisons of measured and modelled demand for two individual homes on four separate days

8.2.5 Cumulative density function

The comparison of the cumulative density function for the group (Figure 8-7) shows that the distribution of the values of the group demand over the year is realistic. The measured data show a higher probability of a zero group demand – arising from the errors in the dataset.

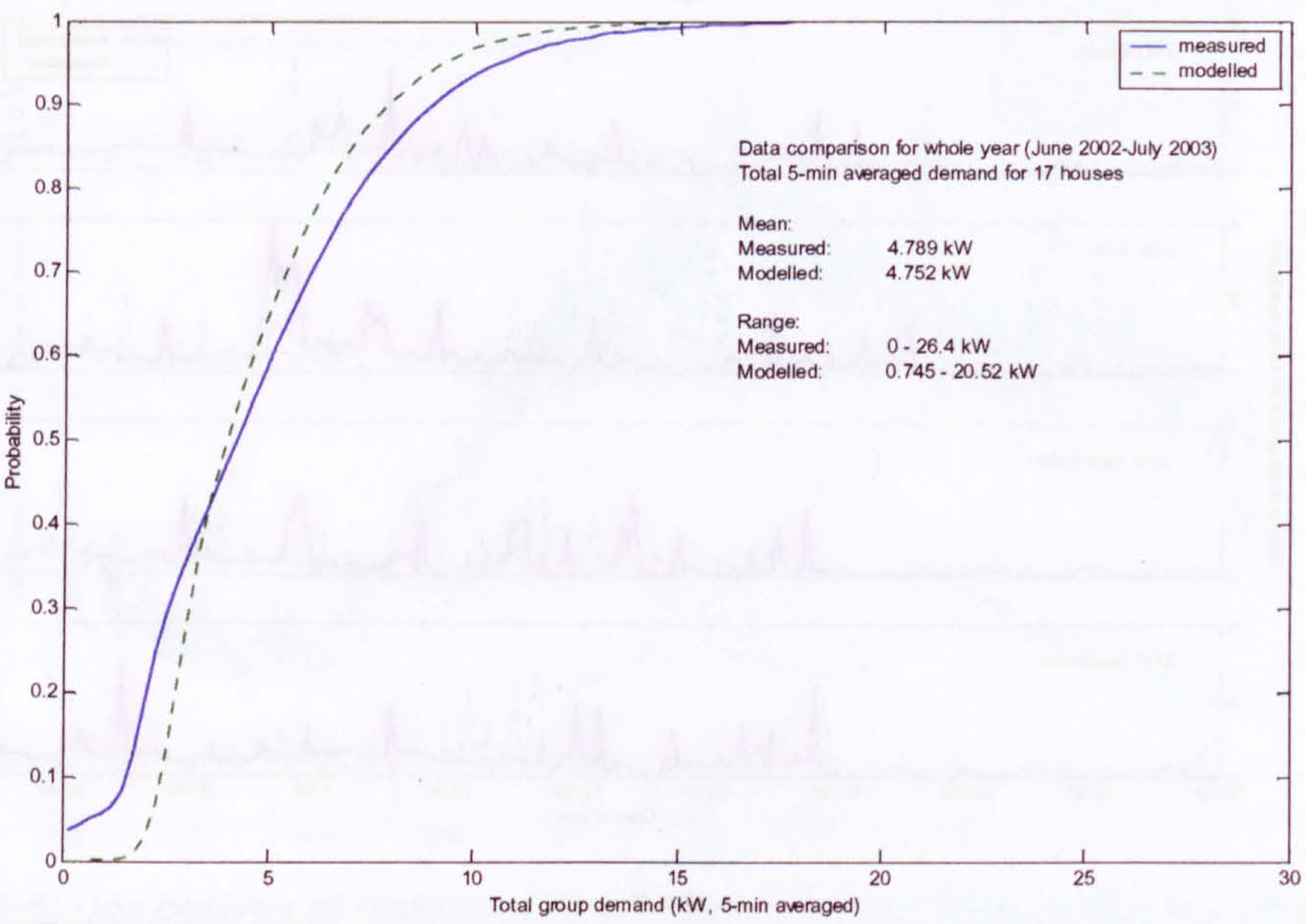


Figure 8-7: Comparison of the measured (solid line) and modelled (dotted line) cumulative density function for the group aggregated demand over 12 months

The modelled and measured distributions both show that there is a 40% probability of the group demand levels being less than 4 kW. Below this value, the model estimates a higher probability of low level demands. Above 4kW, the situation is reversed.

On the whole, the model provides a relatively good representation of the demand distribution on a per house basis (Figure 8-8). The distribution is very close for over half the sample (similar to the upper graph). For the remainder (similar to the lower graph), in most cases the model tends to show a smaller probability of low-level events than appears in the measured data. This may arise partly due to the erroneous negative values in the measured data (set to zero for the comparison) but also due to over-estimating the rating of cooling appliances and for the more continuous miscellaneous demand within the model.

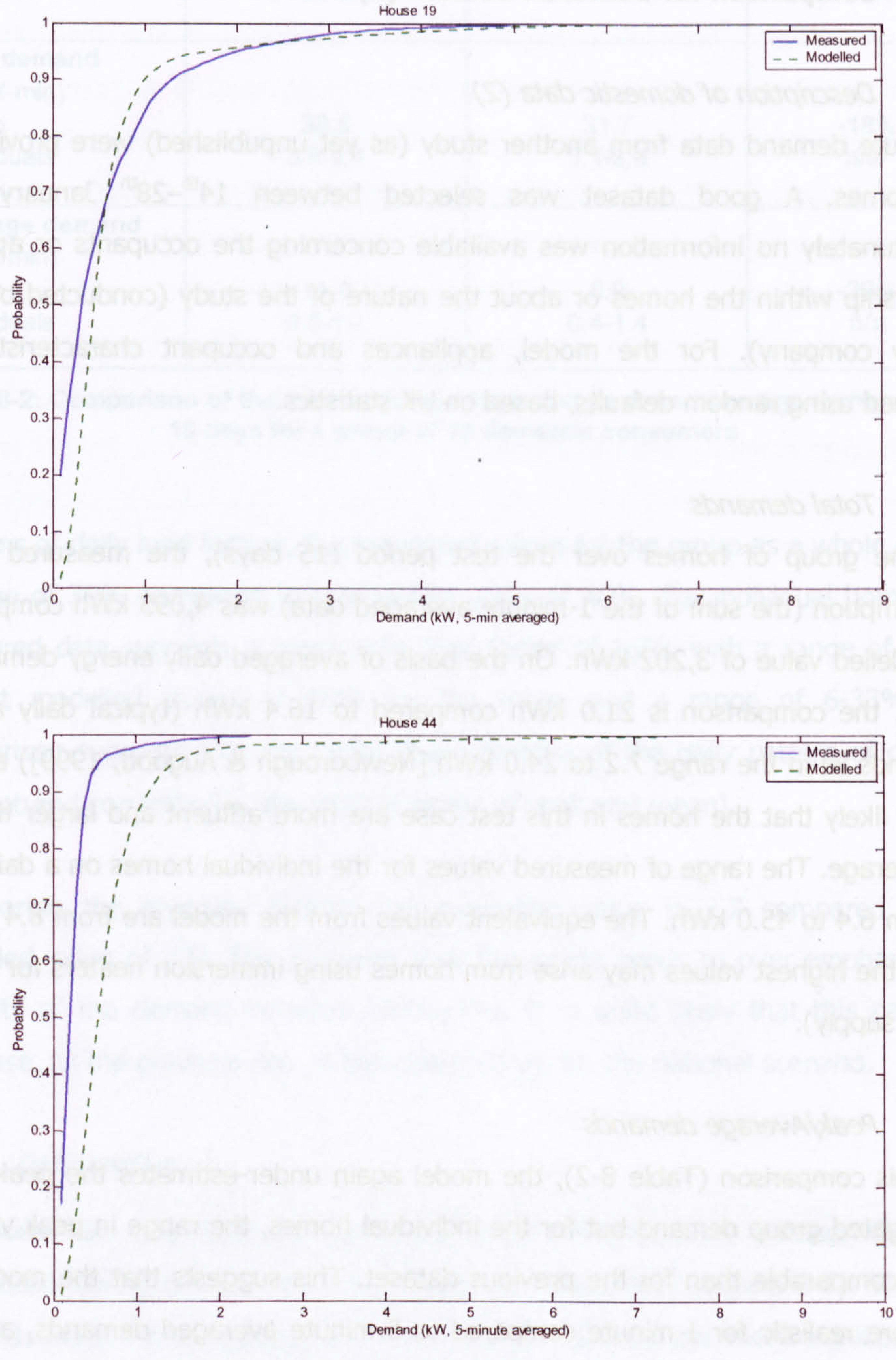


Figure 8-8: Comparison of the measured and modelled cumulative density function for two individual homes over 12 months

8.3 Comparison for domestic dataset (2)

8.3.1 Description of domestic data (2)

1-minute demand data from another study (as yet unpublished) were provided for 13 homes. A good dataset was selected between 14th–28th January 1996. Unfortunately no information was available concerning the occupants or appliance ownership within the homes or about the nature of the study (conducted by a gas supply company). For the model, appliances and occupant characteristics are assigned using random defaults, based on UK statistics.

8.3.2 Total demands

For the group of homes over the test period (15 days), the measured energy consumption (the sum of the 1-minute averaged data) was 4,095 kWh compared to a modelled value of 3,202 kWh. On the basis of averaged daily energy demand per home, the comparison is 21.0 kWh compared to 16.4 kWh (typical daily average demands lie in the range 7.2 to 24.0 kWh [Newborough & Augood, 1999]) and it is highly likely that the homes in this test case are more affluent and larger than the UK average. The range of measured values for the individual homes on a daily basis is from 6.4 to 45.0 kWh. The equivalent values from the model are from 8.4 to 40.4 kWh (the highest values may arise from homes using immersion heaters for the hot water supply).

8.3.3 Peak/Average demands

For this comparison (Table 8-2), the model again under-estimates the peak of the aggregated group demand but for the individual homes, the range in peak values is more comparable than for the previous dataset. This suggests that the model may be more realistic for 1-minute compared to 5-minute averaged demands, although durations for peak events may be too short. The averaged group demand is under-estimated by the model although the range in values for the individual homes appears realistic. This difference, i.e. the relatively worse comparison for group demands but better for individual demands, can arise if the model estimates greater diversity in the timing of peak demand or if the test sample is comprised of relatively more homes with a higher mean demand (again, possibly due to larger houses and more affluent consumers).

Parameter	Measured	Modelled	Variance
Peak demand (kW, 1 min)			
Group	38.5	31.7	-18%
Individuals	3.6-9.4	5.1-9.9	n/a[2]
Average demand (kW, 1min)			
Group	11.4	8.9	-22%
Individuals	0.5-1.4	0.4-1.4	n/a

Table 8-2: Comparison of the measured and modelled peak and average demands over 15 days for a group of 13 domestic consumers

In terms of daily load factors, the measured values for the group as a whole give an average of 39% compared to a modelled value of 40%. For individual homes, the measured data suggests a mean daily load factor of 16%, with a range of 8-30% against modelled values of 15% for the mean and a range of 6-33%. This comparison suggests that the broad characteristics of the daily pattern of demand are captured correctly (i.e. the relative levels of peak and mean).

Comparing the diversity factors, the measured value is 2.7 compared to the modelled value of 2.9. This suggests that the model tends to over-emphasise the diversity of the demand between consumers. It is quite likely that this particular test-case, as the previous one, is less diverse than for the national scenario.

8.3.4 Daily profiles

The model fails to capture the morning and late evening peaks, although the levels of demand during periods of lower activity are reasonable (Figure 8-9). The peak demands occur when lighting and miscellaneous demand are more significant and when socio-economic factors and number of occupants have greater influence. A second run of the model was made assuming that all the homes were large detached properties, occupied by families with ACORN rating B and with a range of electrical appliances assigned. An occupancy profile was adopted that assumed the houses were empty on weekdays between 09:15 and 17:00. Run 2 of the model matches the measured demand well during the morning peak and provides an

[2] No individual comparisons are made for this dataset since the model has used random appliance/end-use assignments

improvement in the late evening demand although still fails to synthesise the demand levels in the late evening. Closer examination of the measured data suggests that many of the homes in the sample have a comparatively high component of constant demand late in the day which the model does not replicate. This demand is again likely to arise from lighting and miscellaneous appliances. Using scaling factors for these components for a lifestyle category B tends to magnify the morning peak but not the demands in the late evening (Figure 5-7). Either the lifestyle scaling factors (taken from the LRG lighting survey) may not be entirely appropriate for miscellaneous demands or the sample homes are unusual in showing high activity in the late evening.

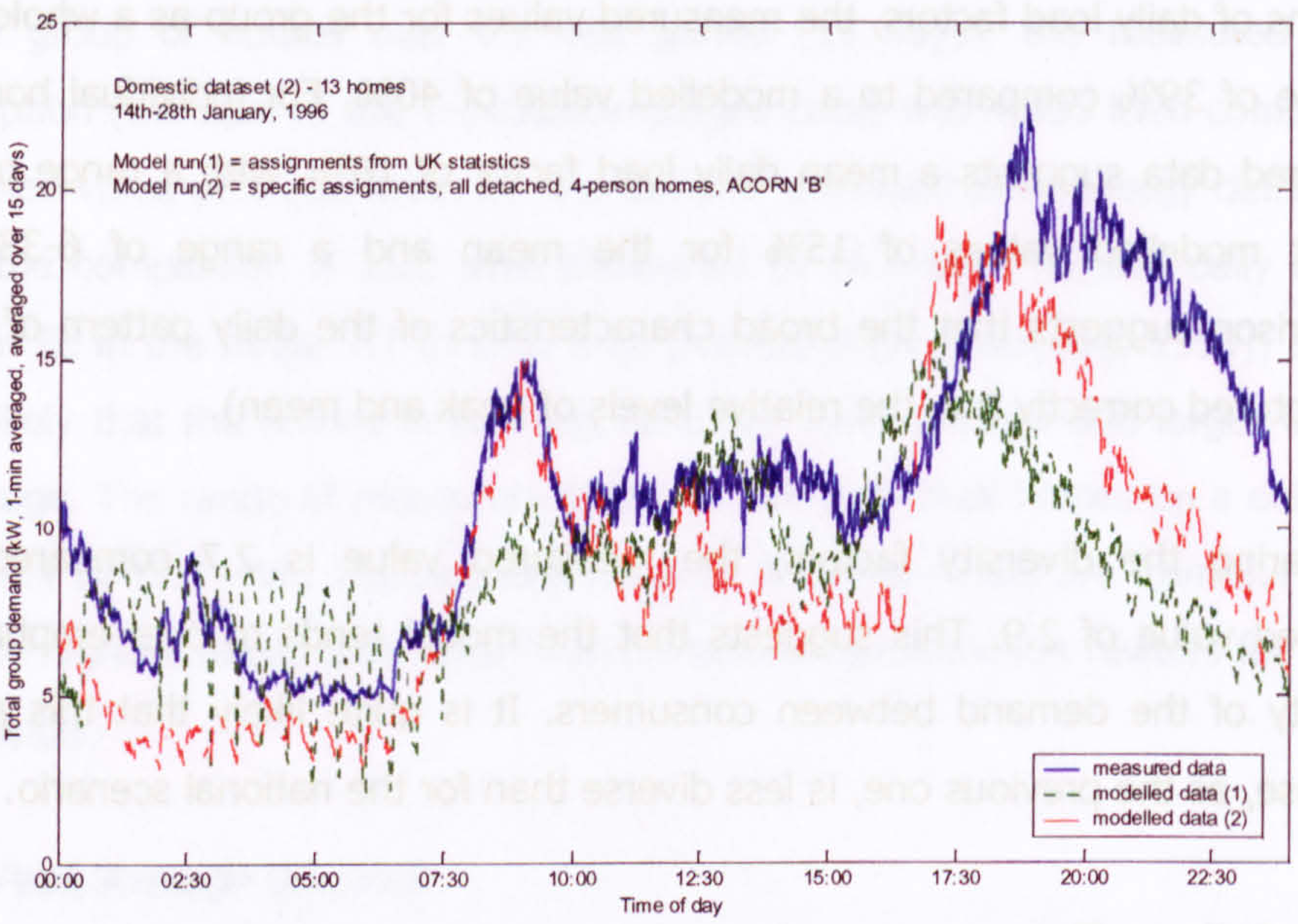
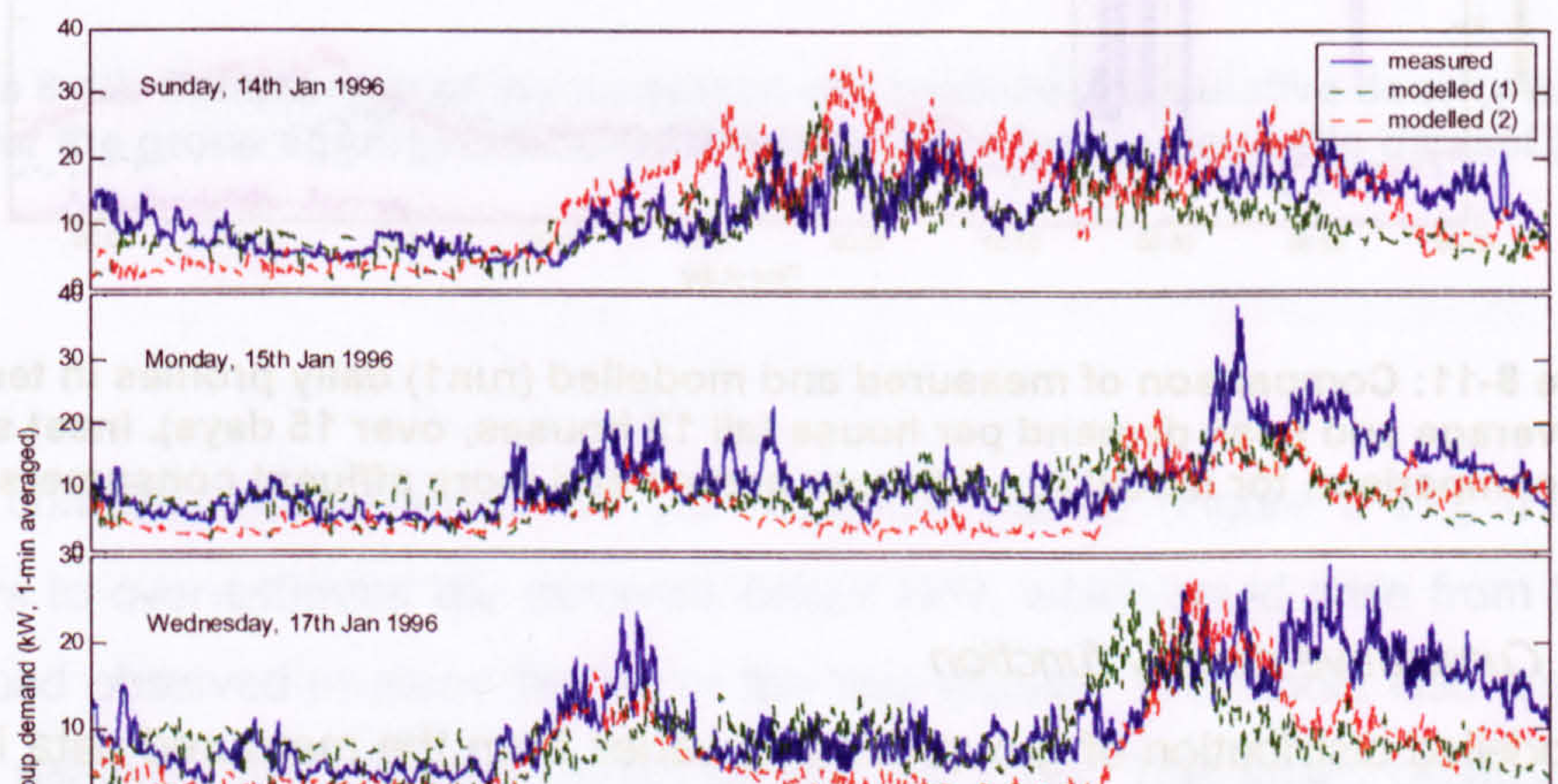


Figure 8-9: Comparison of measured and modelled average daily profile for the aggregated demand of all the test case homes over all 15 days for dataset (2)

The significant swings in the modelled demand up to 07:30 probably arise from the assignment to one or more homes in the first test run of off-peak space heating. The modelled storage heater demand is switched in and out for varying periods in each half-hour, assuming the entire heating load acts as a single unit. It is clear that the model could be improved if the heating events were allowed to extend from one half-hour into the next and each heater were considered as a single load. (No consumers have been allocated demand for space heating in run 2).

Based on a comparison of profiles for individual days (different days of the week, Figure 8-10), apart from the late evening peak (as discussed earlier), the model appears to capture the group demand profile well for weekends, when the demand is more diversified. On weekdays, the model tends to under-estimate the morning peak (improved by corrections for larger affluent homes) but tends to over-estimate the demands around 16:00. This is similar to the comparisons made for the first domestic test case. For run 2, the occupancy profile used for all the homes on weekdays causes a lower group demand than the measured data. The upward scaling for above-average occupancy (4 people per home) accentuates the cooking demand around midday at weekends. However, the model appears to be performing adequately in broad terms for scale and pattern of demand. Without detailed information about the test case, it is difficult to identify whether the differences arise from unusual behaviour in the measured data or shortfalls in the model.



8-10: Comparison of measured and modelled daily profiles on four specific day types for the aggregated demand of all the test case homes

When the characteristics for the individual daily profiles are compared for all the homes over the 15 test days (figure 8-11), the results also show a reasonable comparison. The higher modelled peak demands in the early morning most likely arise from the assignment of off-peak space heating. It is clear that the model fails to trigger large events late in the day which occur in the test case. Scaling the lighting and miscellaneous demand for higher occupancy and lifestyle index B improves this representation somewhat (inset, Figure 8-11).

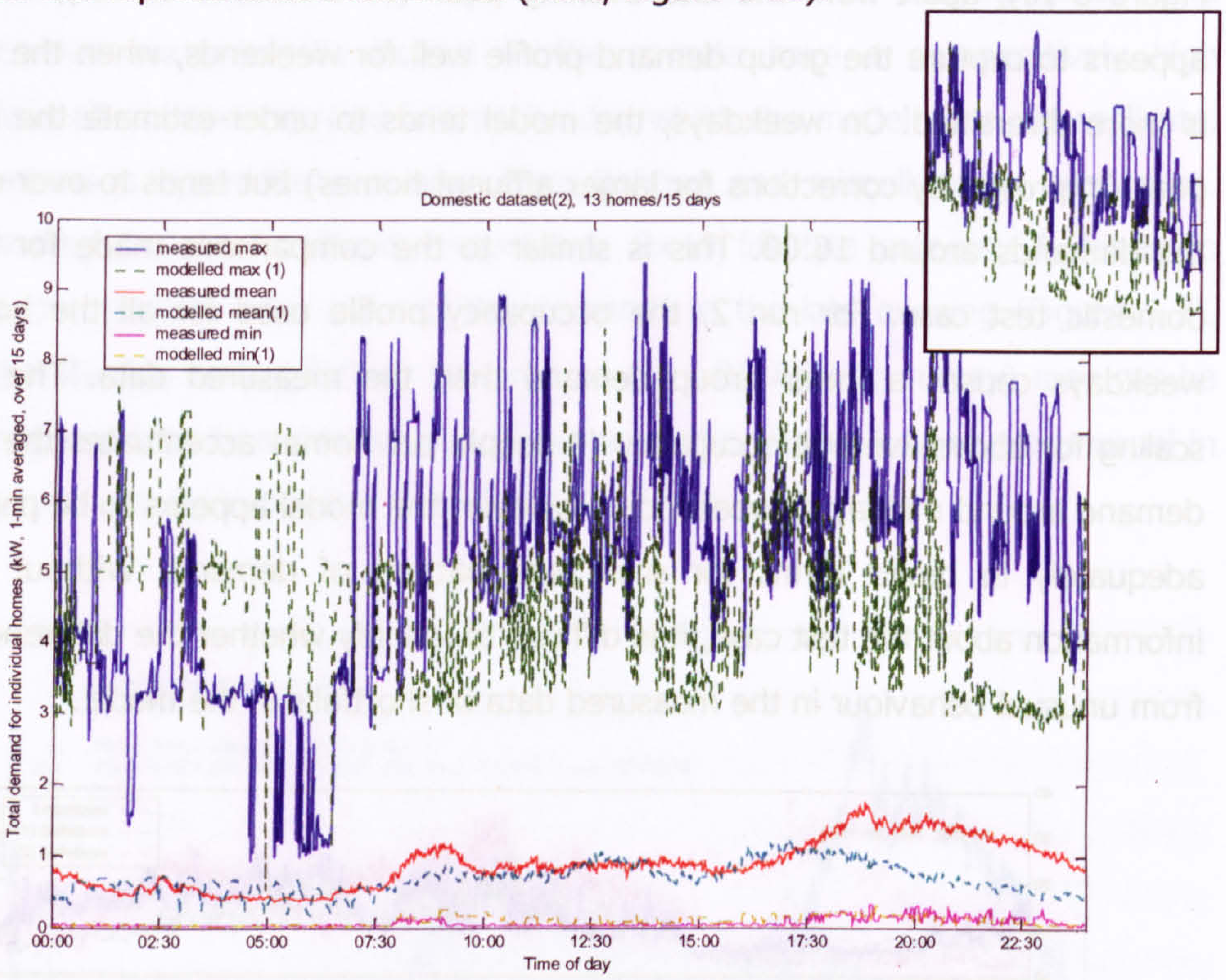


Figure 8-11: Comparison of measured and modelled (run1) daily profiles in terms of the average and peak demand per house (all 13 houses, over 15 days). Inset shows comparison for model run 2 (larger homes and more affluent consumers)

8.3.5 Cumulative density function

The modelled distribution of group demand varies from the measured data in many respects (Figure 8-12). The measured demands for the test group show an unusually large base load in many homes (as much as 500W), causing the probability curve for the group demand to be offset. The first run of the model presents a relatively high distribution of low level events, matching the measured data with a 20% probability of demands being 6 kW or less. Thereafter, the modelled group demands show a higher probability of mid-range level (6-15 kW) events, which may arise from the space heating load during the early morning.

For the second run of the model, ignoring the difference in base loads, the distribution of demand is similar up to around 10kW, above which the model estimates fewer demand events. This is probably as a result of the under-estimation of the miscellaneous and lighting peaks during the late evening.

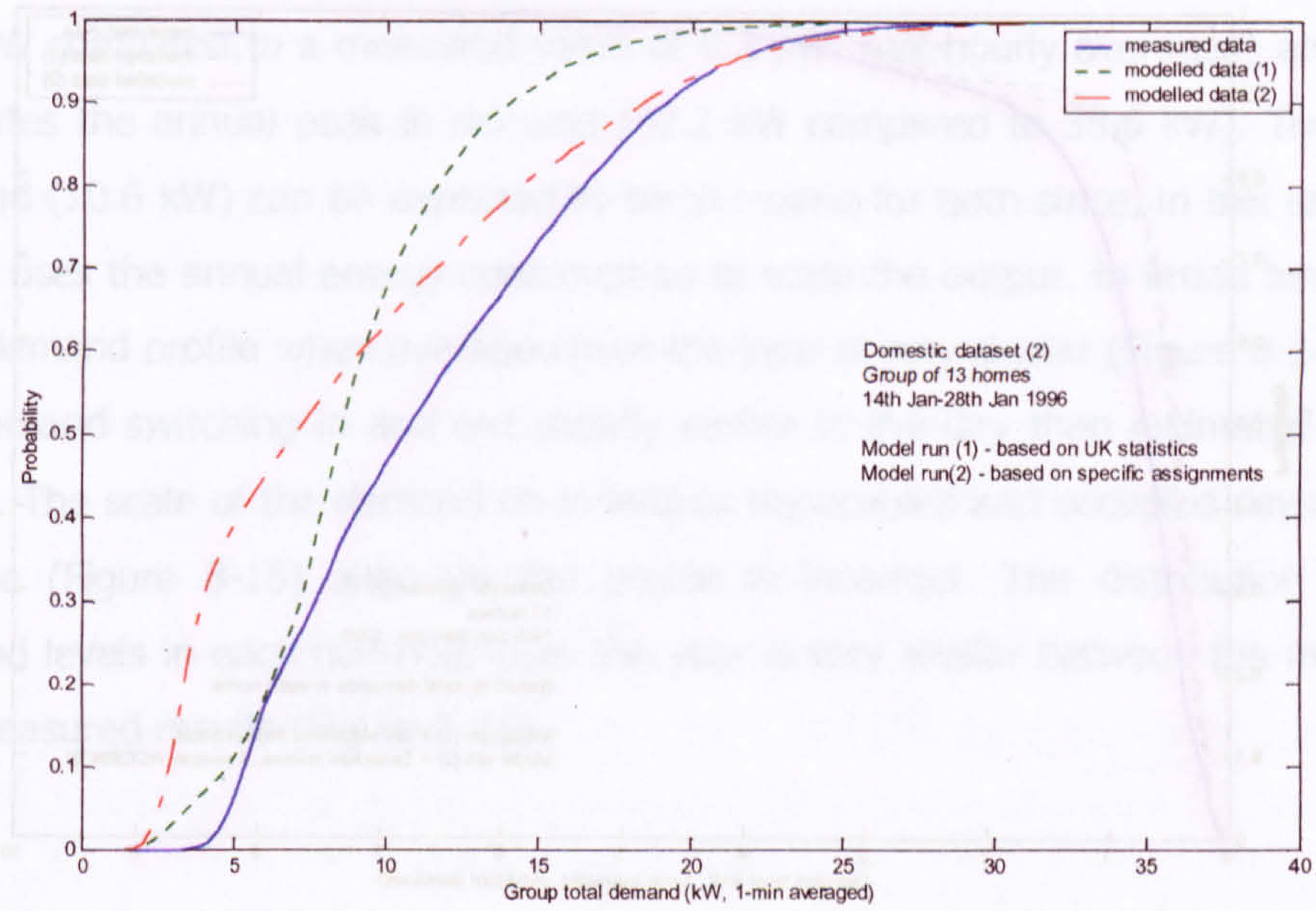


Figure 8-12: Comparison of the measured and modelled cumulative density function for the group aggregated demand over 15 days for the domestic dataset (2)

When comparisons are made for the individual homes (Figure 8-13), the model appears to over-estimate the demands below 1kW, which could arise from the high base-load observed in many homes in the test sample. The model also appears to create relatively few demand events between 1-2 kW. This arises because events tend to be triggered in all homes, based on identically rated appliances. The output might be improved by varying the ratings in standard duty cycles. Based on demand distribution, there is little difference between the two runs of the model, possibly with higher events arising from space heating compensating for the fewer high level events in the late evening in run 1.

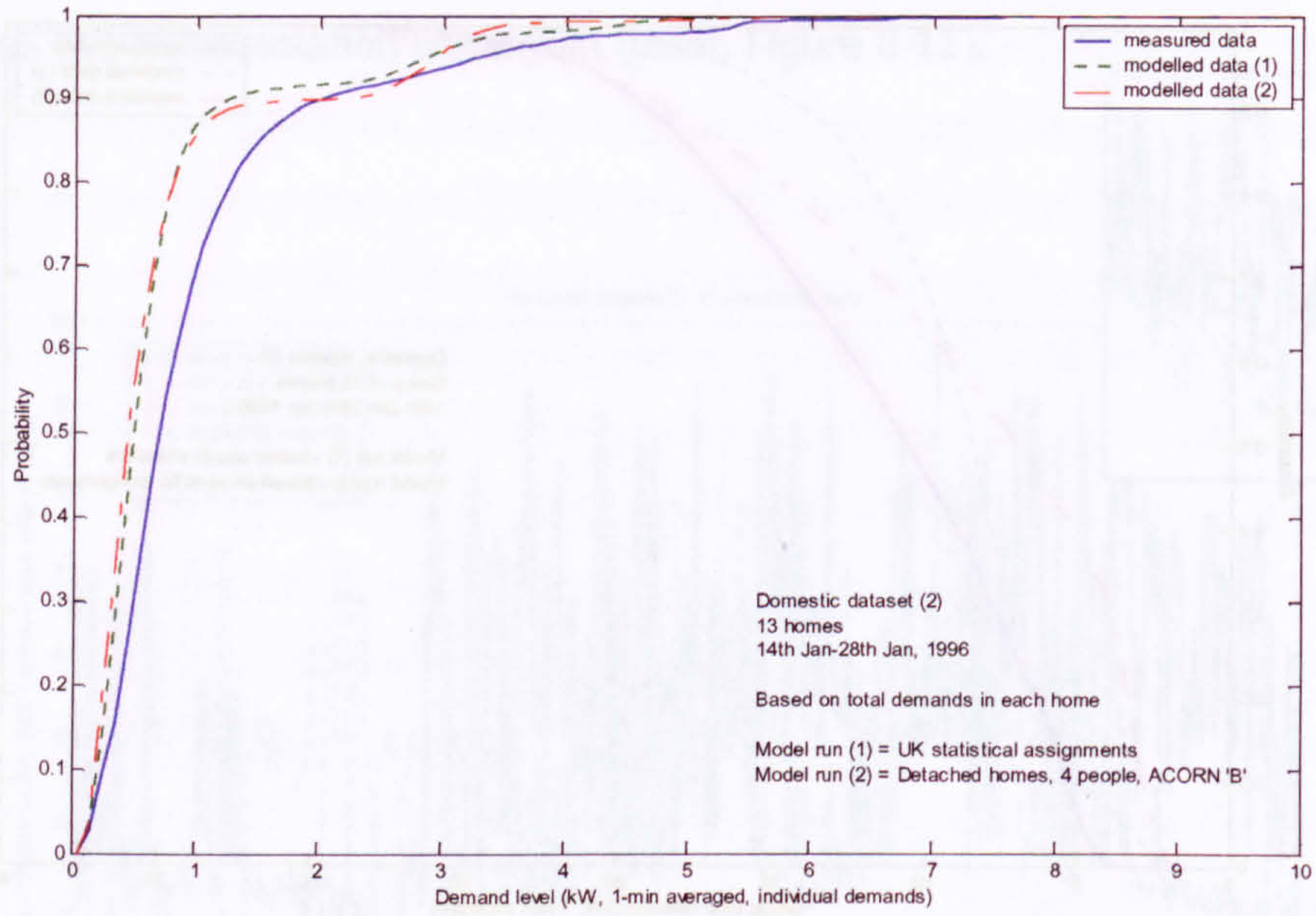


Figure 8-13: Comparison of the measured and modelled cumulative density function for the demand in the 13 individual homes over 15 days for the domestic dataset (2)

8.4 Comparison for non-domestic data – schools

8.4.1 Non-domestic data – schools

Half-hourly averaged data for primary and secondary schools in the Nottinghamshire area were provided for comparison with the non-domestic load model output. For most of the schools demand data are available from April 2001 until August 2003. In the previous chapter, a medium sized school was used to examine the approach proposed for non-domestic consumers. Here, two further examples are chosen, one a small special school and the other a very large comprehensive (which examines the application of the approach for consumers with demand above the 100kW threshold).

8.4.2 Comparison for a small special school

Half-hourly demand data from a small school that caters for disabled students were used for comparison with the output from the non-domestic model. This school has a floor area of just over 4,000 m^2 and an annual energy consumption of 93 MWh. The latter was the only input parameter used for the model apart from the start and end dates for the test run.

Based on a complete year, the model slightly under-estimates the base load value (2.3 kW compared to a measured value of 0.2 kW, half-hourly averaged) and over-estimates the annual peak in demand (42.2 kW compared to 38.6 kW). The mean demand (10.6 kW) can be expected to be the same for both since, in this case, the model uses the annual energy consumption to scale the output. In broad terms, the daily demand profile when averaged over the year is very similar (Figure 8-14), with the demand switching in and out slightly earlier in the day than estimated by the model. The scale of the demand on individual unoccupied and occupied days is very realistic (Figure 8-15) although the profile is incorrect. The distribution of the demand levels in each half-hour over the year is very similar between the modelled and measured results (Figure 8-16).

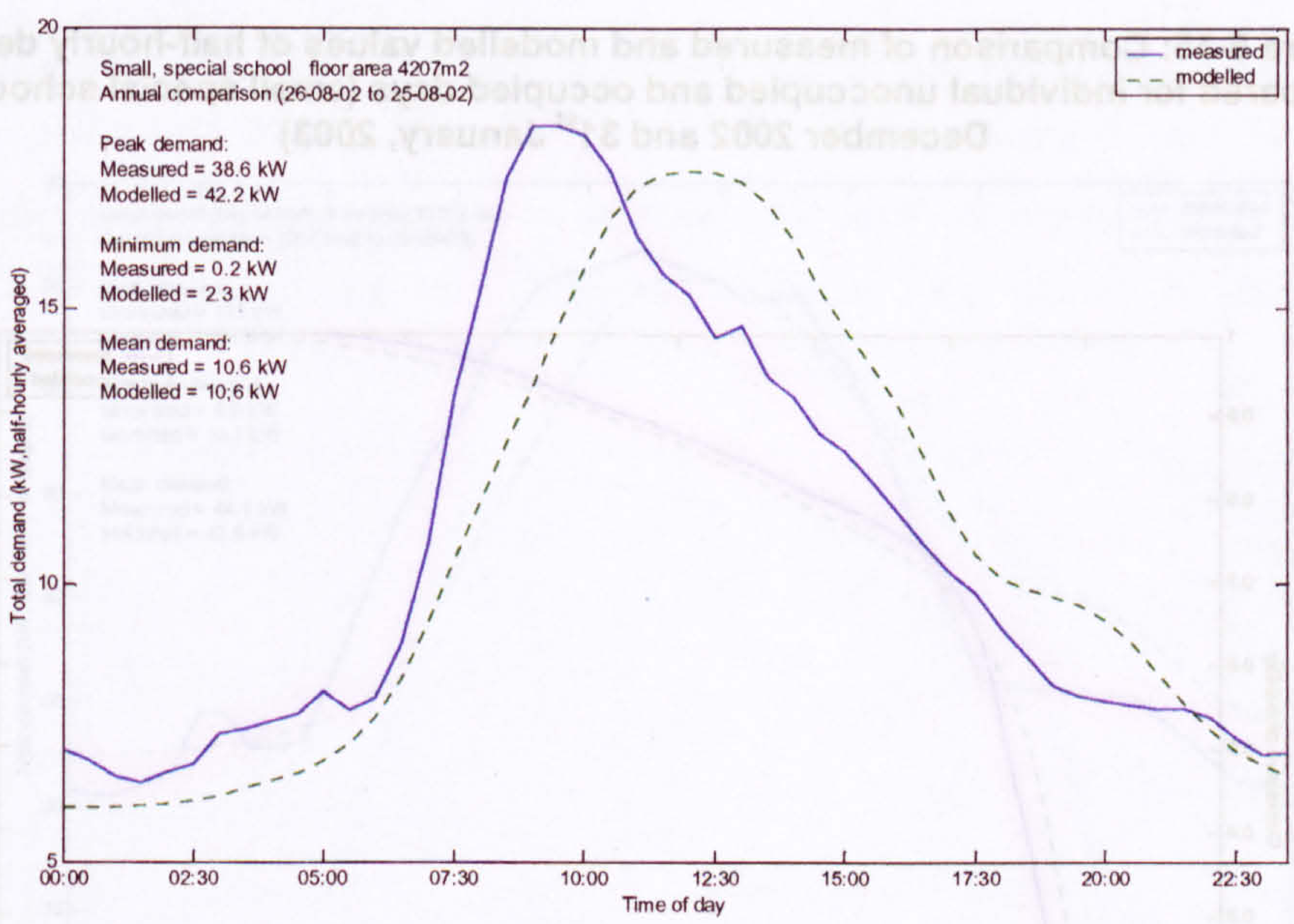


Figure 8-14: Comparison of measured and modelled values of half-hourly demand compared as an annually averaged daily profile (small special school, 26th August 2002 to 25th August 2003)

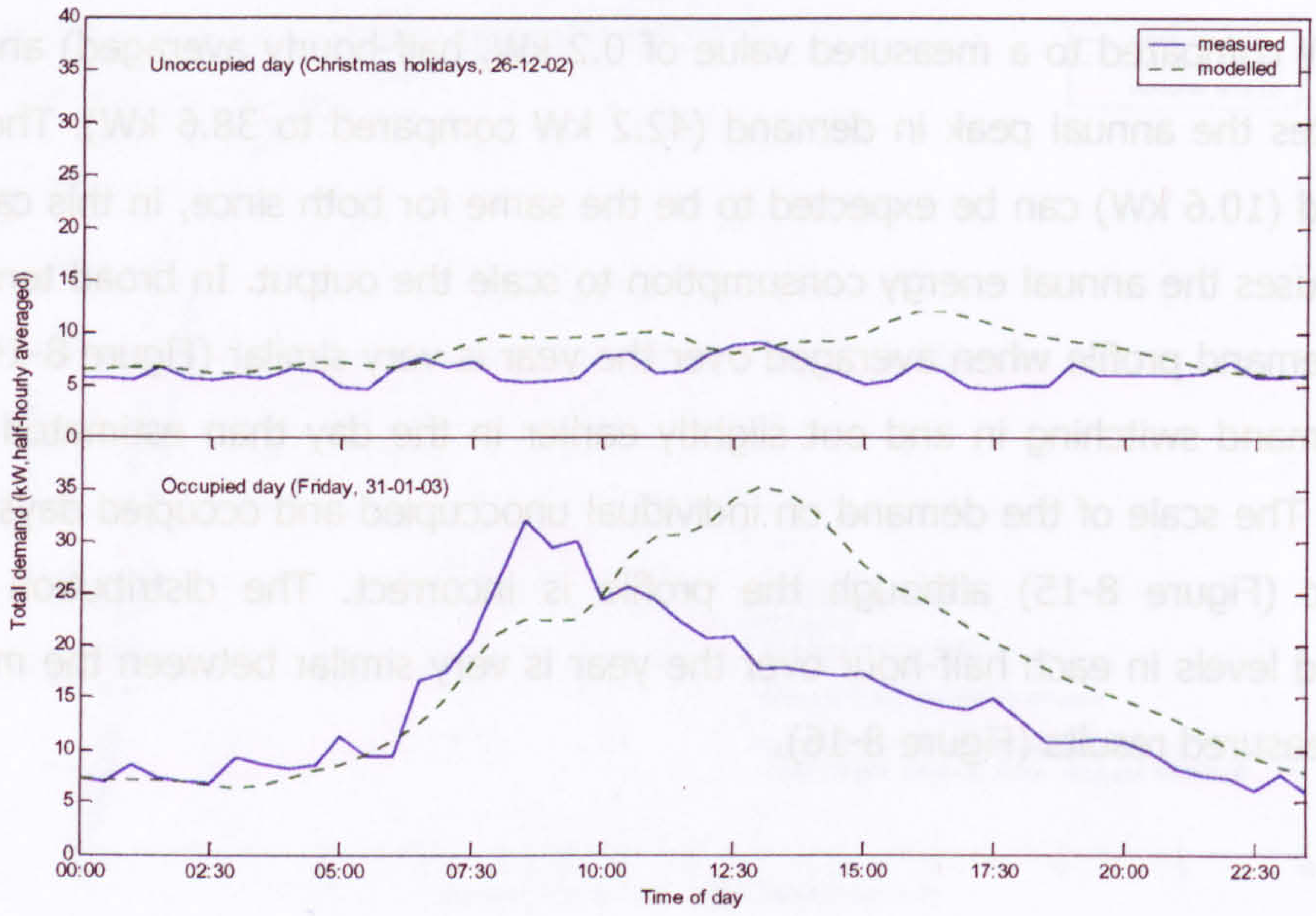


Figure 8-15: Comparison of measured and modelled values of half-hourly demand compared for individual unoccupied and occupied days (small special school, 26th December 2002 and 31st January, 2003)

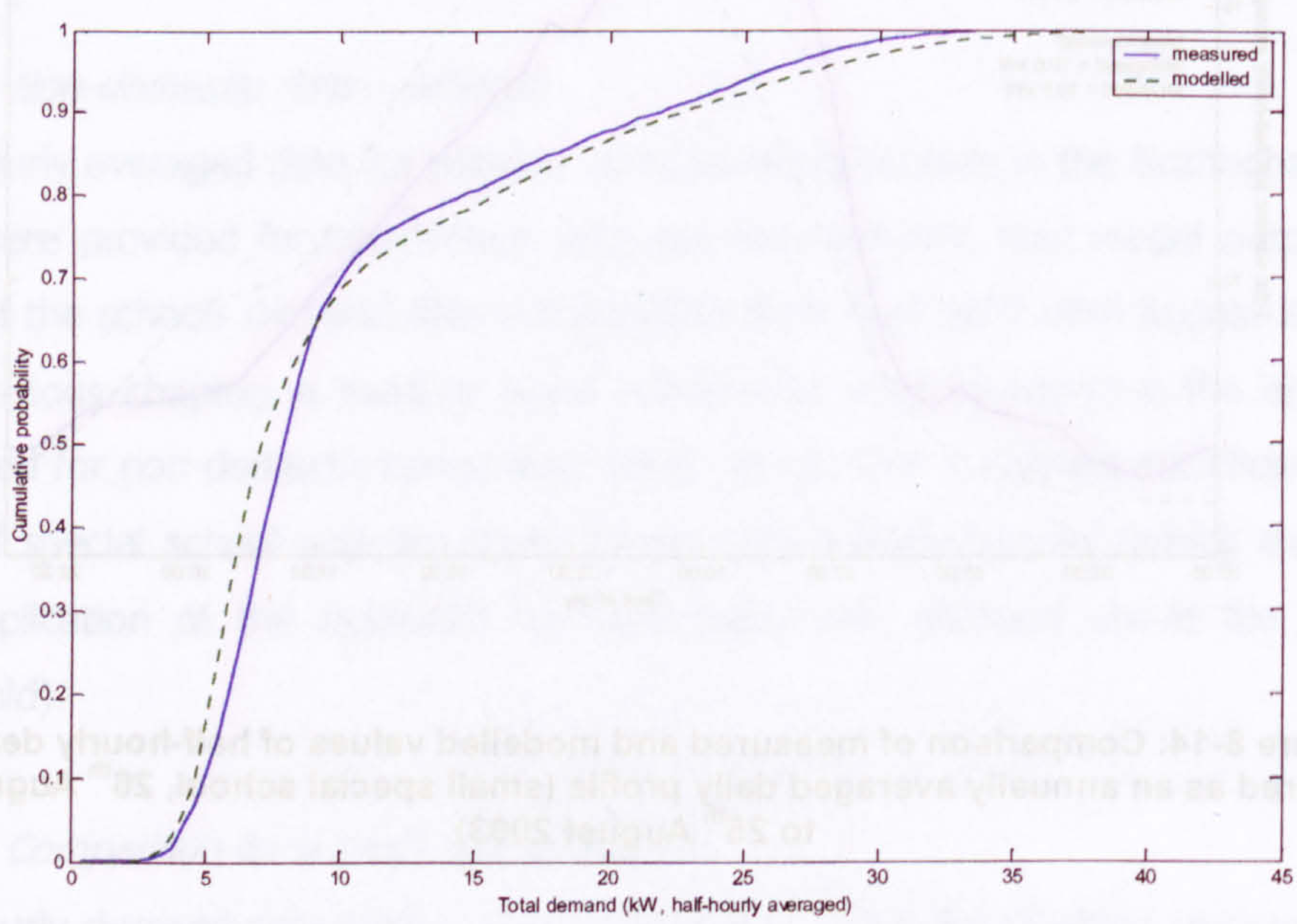


Figure 8-16: Comparison of measured and modelled values of the cumulative probability of the half-hourly demand levels throughout a year (small special school, 26th August 2002 to 25th August 2003)

8.4.3 Comparison for a large sized comprehensive school

The second school used for the comparison against the non-domestic model is a large state comprehensive school, with a floor area of over 13,000 m^2 and an annual energy consumption of almost 400 MWh. As in the previous example, the measured demand tends to increase and decrease slightly earlier in the day than the model predicts. This arises since the model is based on the daily profiles for the Swedish schools, which start and finish slightly later than their UK counterparts. The non-domestic model might benefit from a slight adaptation of the profile. However, as before, the scale and general shape of the demand profile is realistic, compared annually (Figure 8-17) and for individual days (Figure 8-18). The demand distribution for this school shows that very few half-hourly demand values lie between 40-80kW whilst the model provides a more even distribution (Figure 8-19).

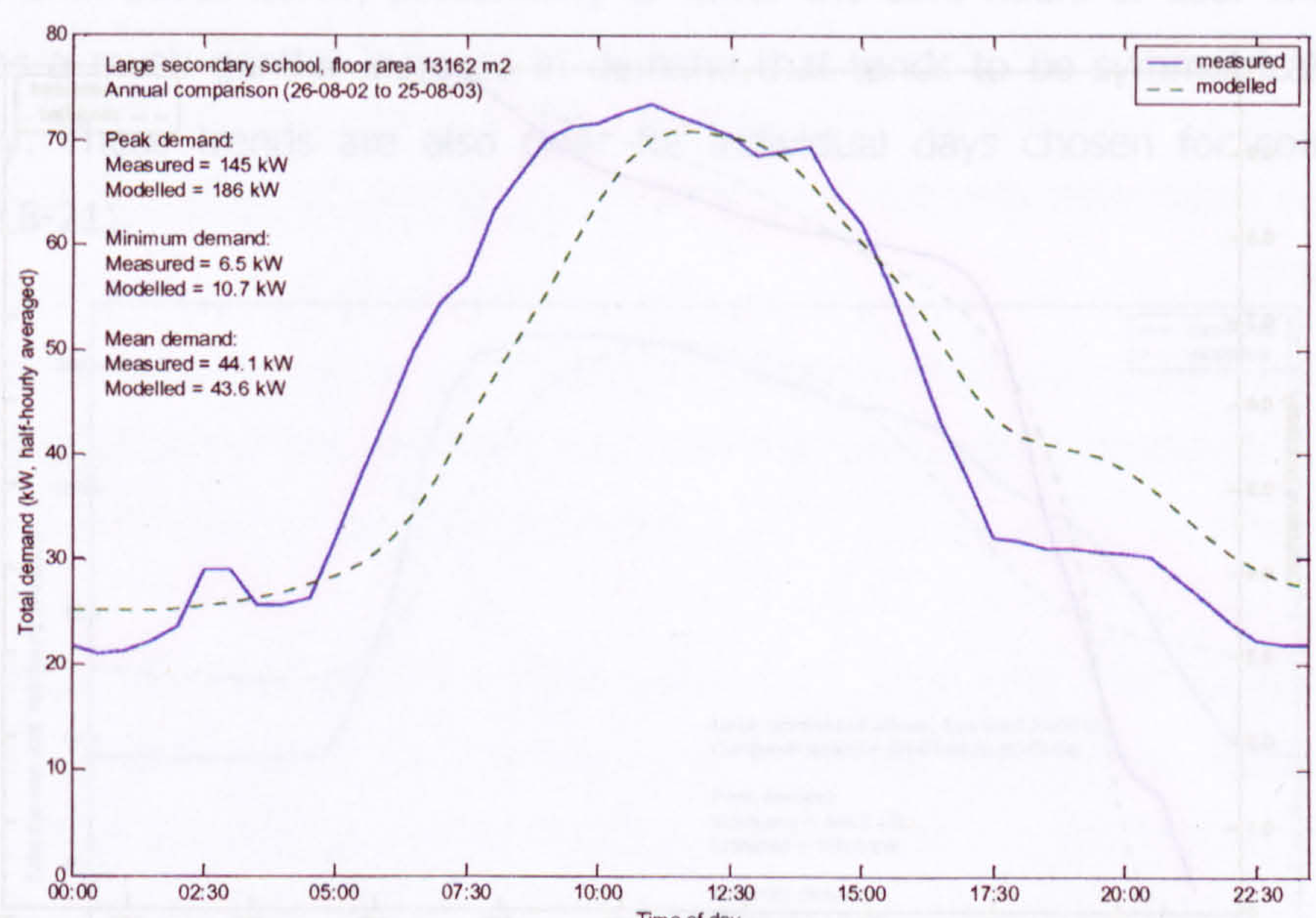


Figure 8-17: Comparison of measured and modelled values of half-hourly demand compared as an annually averaged daily profile (large secondary school, 26th August 2002 – 25th August, 2003)

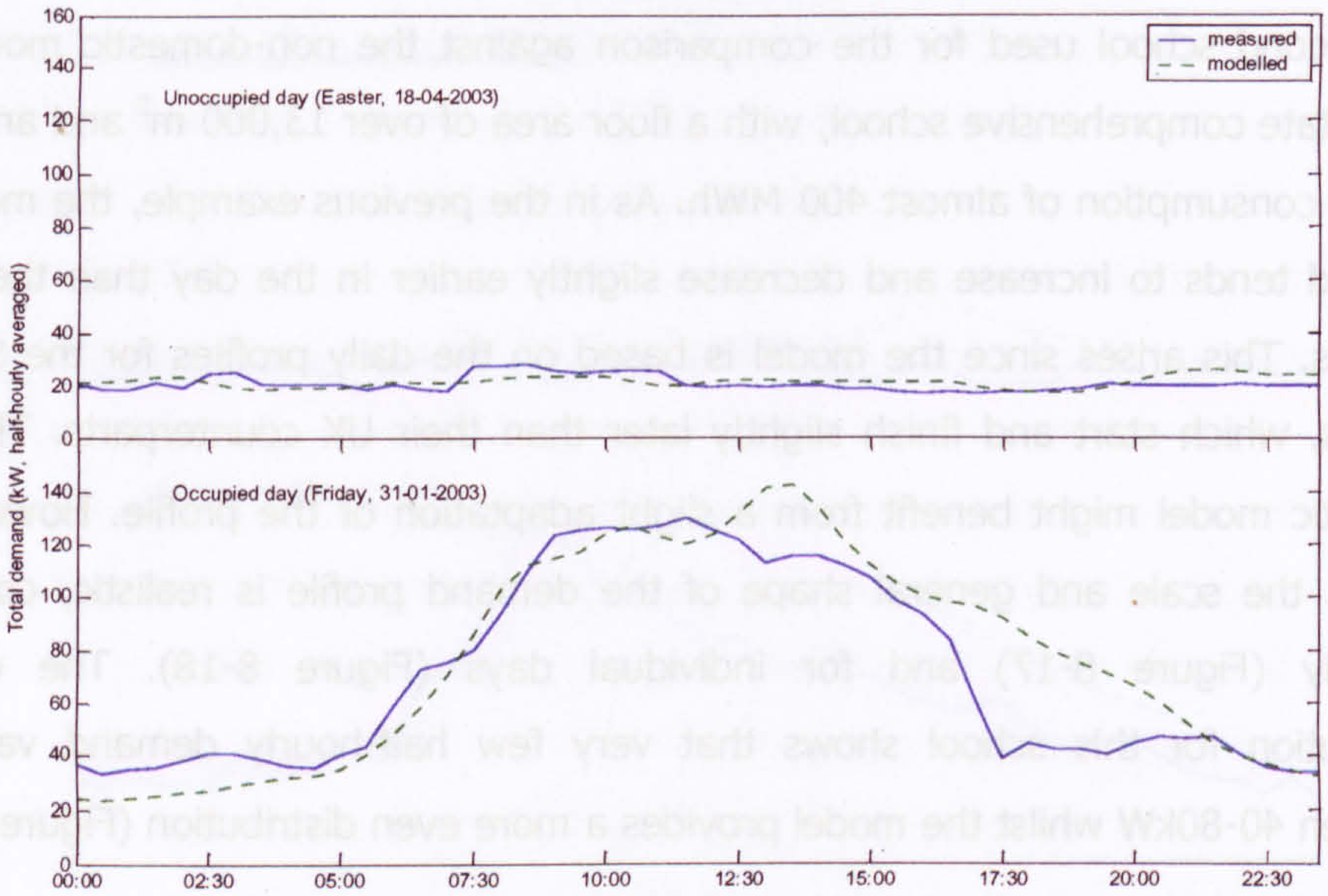


Figure 8-18: Comparison of measured and modelled values of half-hourly demand compared for individual unoccupied and occupied days (large secondary school, 18th April and 31st January, 2003)

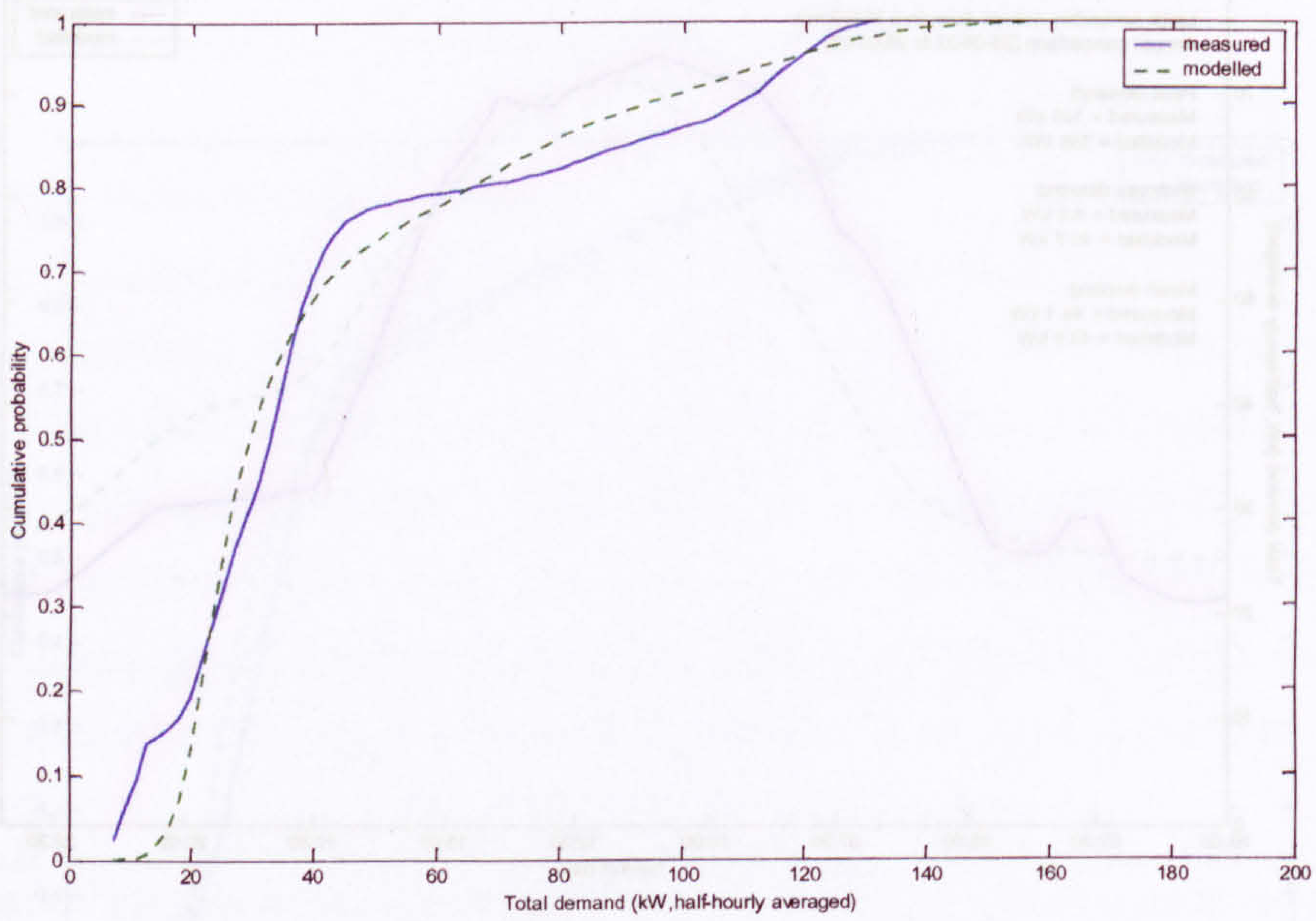


Figure 8-19: Comparison of measured and modelled values of the cumulative probability of the half-hourly demand levels throughout a year (large secondary school, 26th August 2002 to 25th August 2003)

8.5 Comparison for non-domestic data – offices

Demand data were provided for a building used as the headquarters of a large banking group in central Leicester. The demand is based on a half-hourly average, throughout 2003. The total office space is estimated at 3,400 m^2 and the total annual energy consumption is just over 808 MWh. The latter, together with the start and end dates of the test run (1st January to 31st December, 2003) were used in the model. It was also assumed that the offices are mechanically ventilated, use gas for space and water heating and that the offices do not include cooking facilities. This example again examines the value in using the suggested approach for larger (peak demand > 100kW) non-domestic consumers.

The model provides a reasonable scale of daily demand. Base load demand levels tend to be over-estimated (approximately 72 kW compared to 59 kW, Figure 8-20). The measured data show a sharp ramping of demand at around 05:00 with a slow decline until about 20:00, presumably to cover the core hours of use. The model provides a much gentler increase in demand that tends to be symmetrical around mid-day. These trends are also clear for individual days chosen for comparison (Figure 8-21).

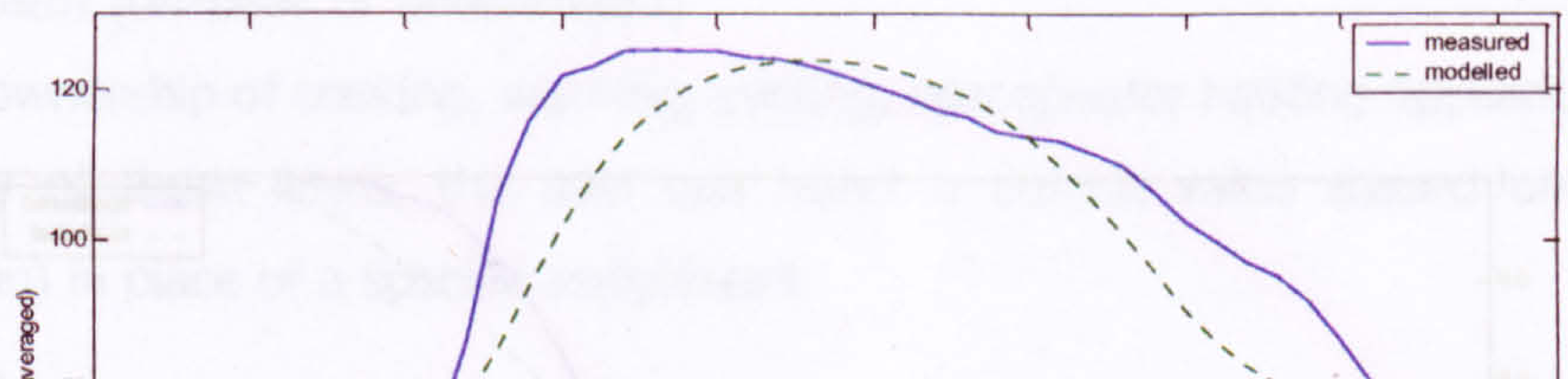


Figure 8-20: Comparison of measured and modelled values of half-hourly demand compared as an annually averaged daily profile (large office block, 1st January – 31st December, 2003)[3]

[3] The minimum demand of 1.0 kW only occurs on 2 days, possibly selected for shutdown maintenance. A more typical minimum demand for these offices is around 50 kW.

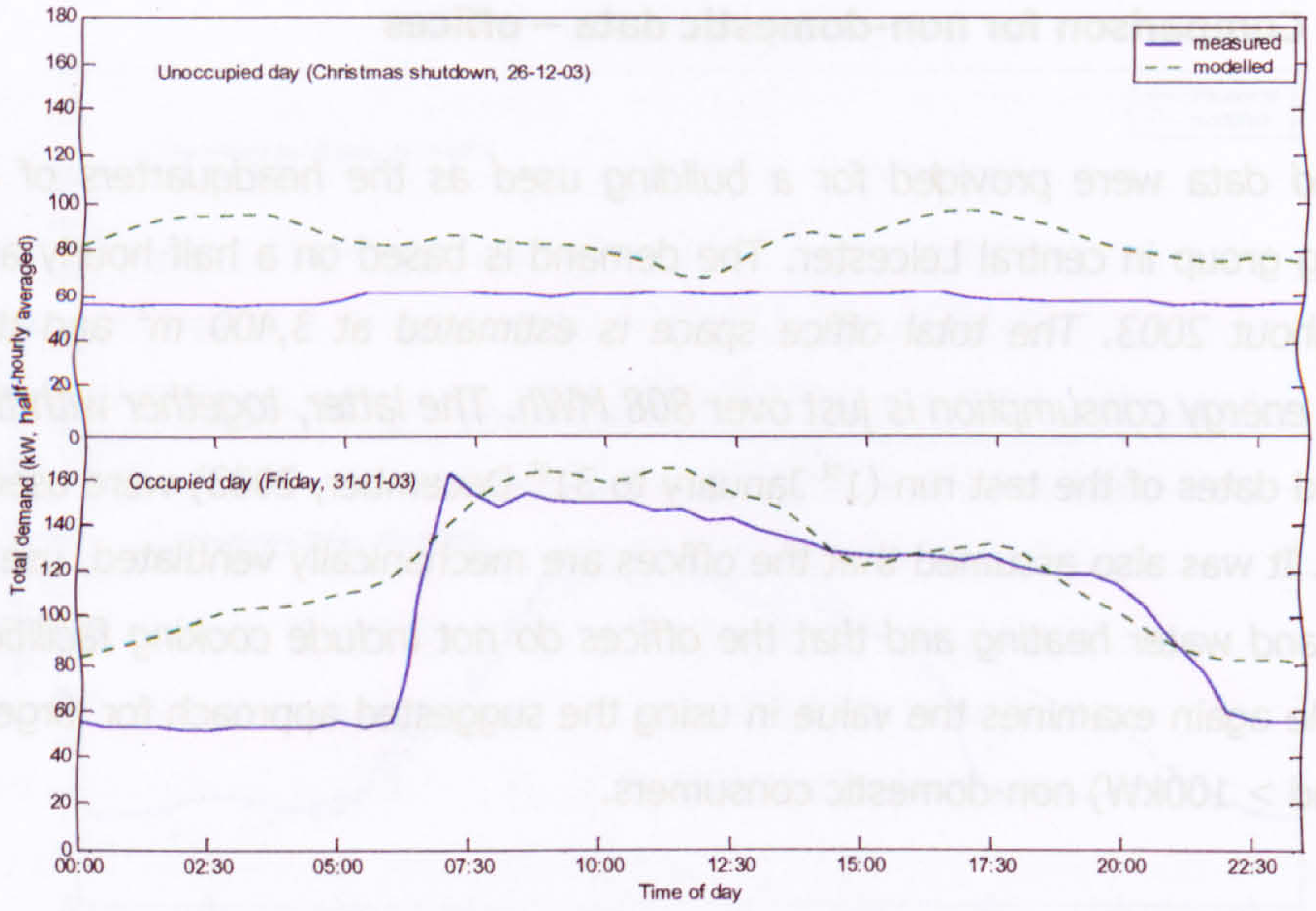


Figure 8-21: Comparison of measured and modelled values of half-hourly demand compared for individual unoccupied and occupied days (large office block, 26th December and 31st January, 2003)

Steps in the measured distribution of demand (Figure 8-22) suggest that discrete loads might be operating between 50-60 kW and 100-120 kW. The model estimates a slightly more even distribution of load but in general the distribution compares favourably.

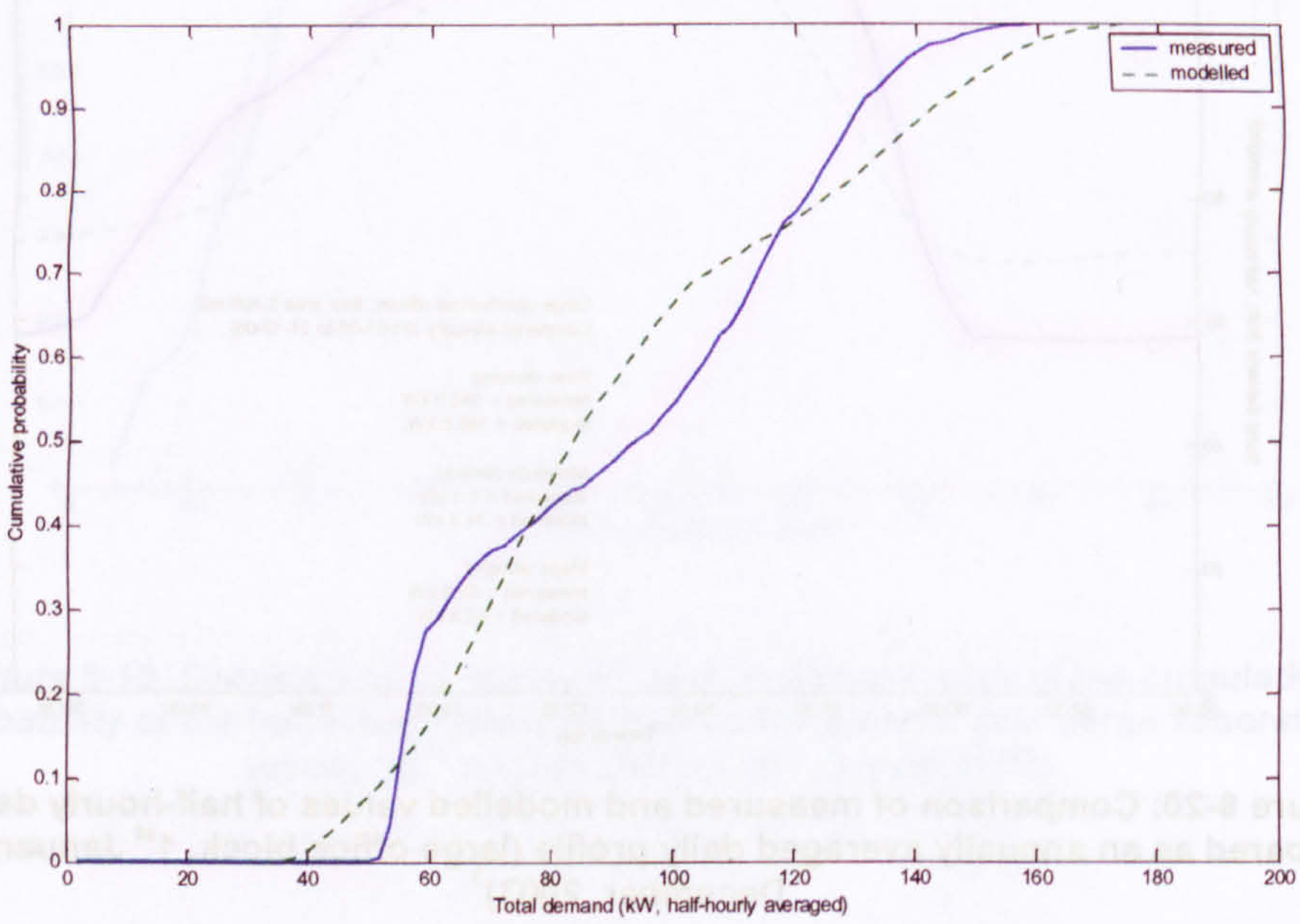


Figure 8-22: Comparison of measured and modelled values of the cumulative probability of the half-hourly demand levels throughout a year (large office block, 1st January to 31st December 2003)

8.6 Operational factors

8.6.1 MATLAB version of the model – required user inputs

To provide the comparisons with measured data, the load models as described in the earlier chapters were coded in MATLAB Student Version 6.0 running on a laptop PC (1.9 GHz, 240 MB RAM). A rudimentary user interface was created to allow data input to the model (Figure 8-23 to 8-26). The minimum required user input defines:

- the start and stop dates for the test run
- whether the consumer(s) are domestic or non-domestic

In the current version of the coded load model, the user may opt to create a test run for a batch of domestic consumers, with a defined group size, or for a single consumer or group (also of user defined size) with an identical description. In the former case, all values for the consumer descriptors and appliance ownership are assigned randomly, using national statistics. In the latter, the user can opt to define the following:

- floor area
- number of occupants
- occupant lifestyle factor and income
- tariff (off-peak or unrestricted)
- ownership of cooking, washing, cooling, space/water heating appliances

For any of these items, the user can select a default value (based on random selection) in place of a specific assignment.

For the non-domestic load, the user may select an activity from shops, offices, schools, hotels, places of worship and industrial categories. Further sub-classifications are also required although in all cases, the user may opt for a random selection if activity is unknown. The user may input specific values for the associated floor area and annual electricity consumption or may opt for a random selection based on a distribution appropriate to the business activity. The user may also choose to define holiday periods and whether or not electricity is used as the fuel for cooking and water/space heating.

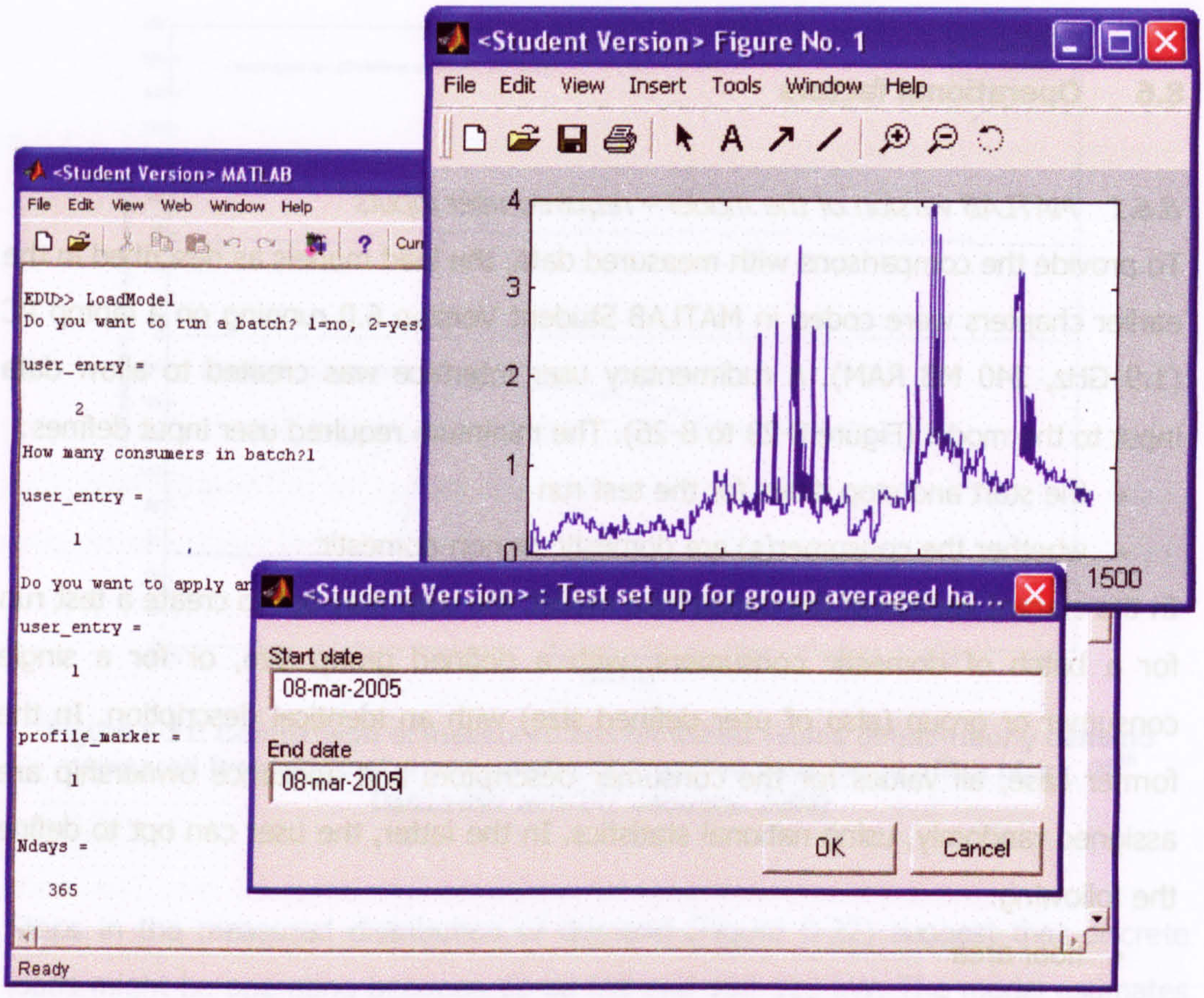


Figure 8-23: Screenshots of MATLAB version of the load model used for validation purposes

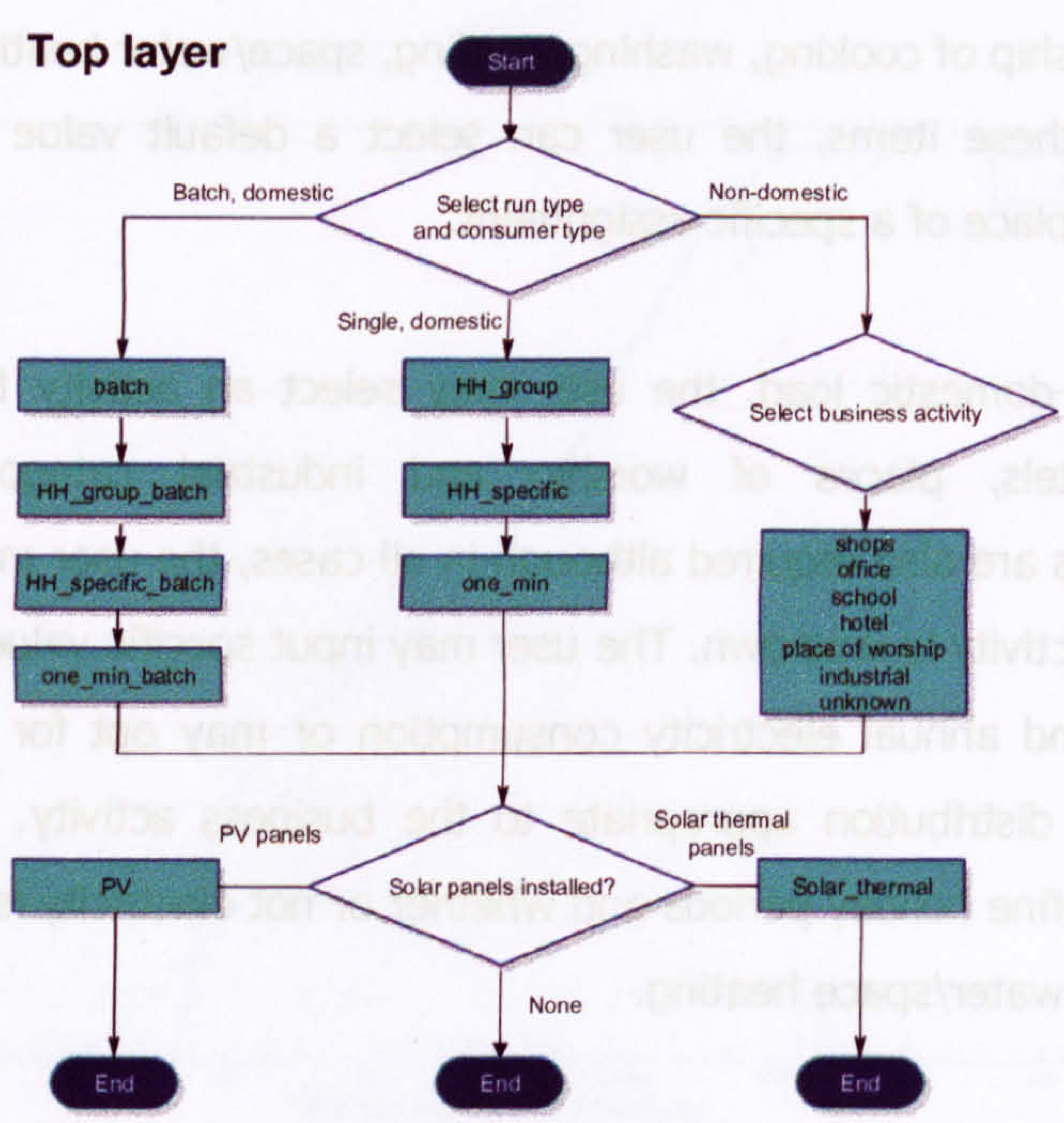


Figure 8- 24: Top layer flow chart for MATLAB version of the load model

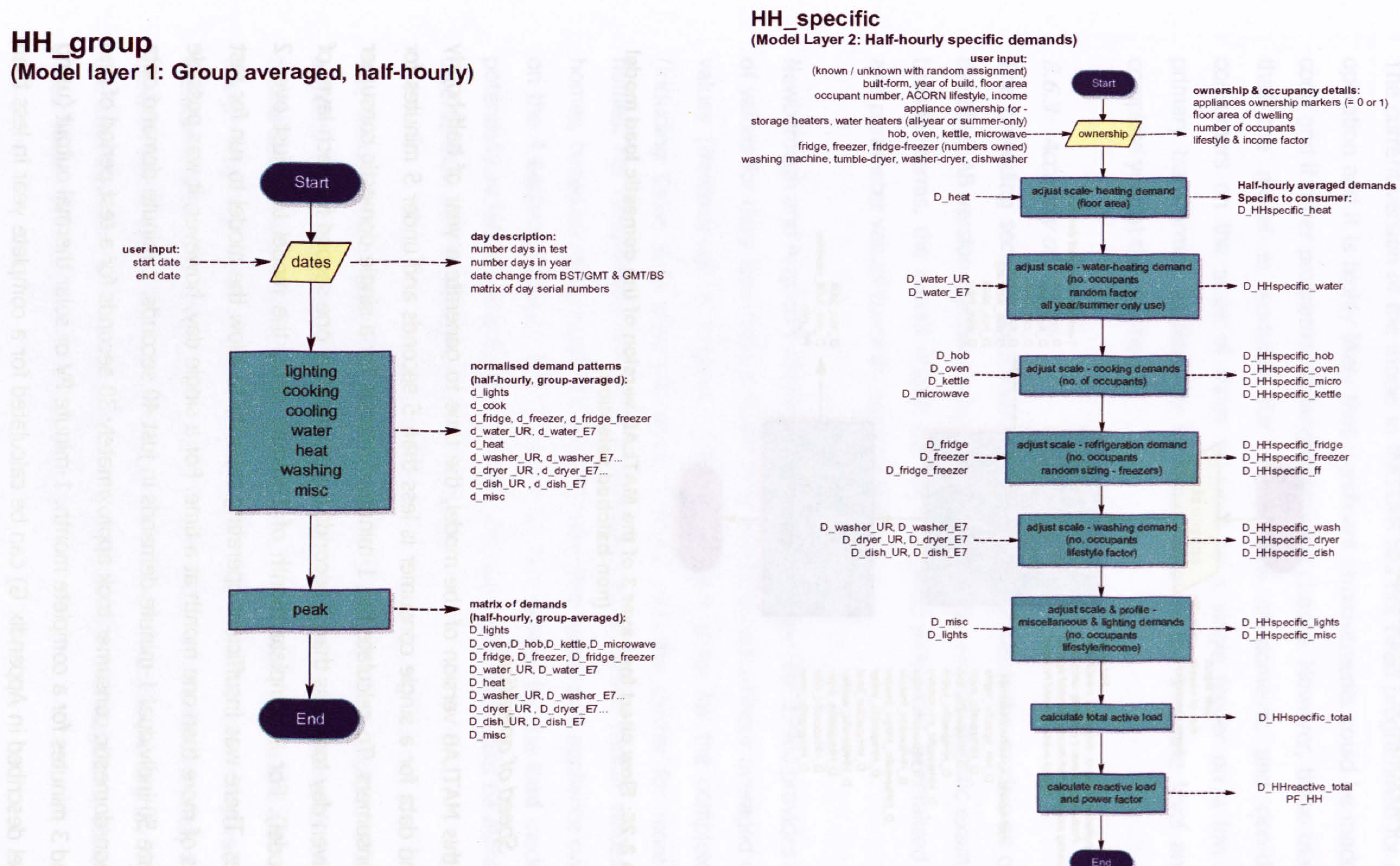


Figure 8-25: Flow charts for Layers 1 and 2 of the MATLAB version of the domestic load model (non-batched selection)

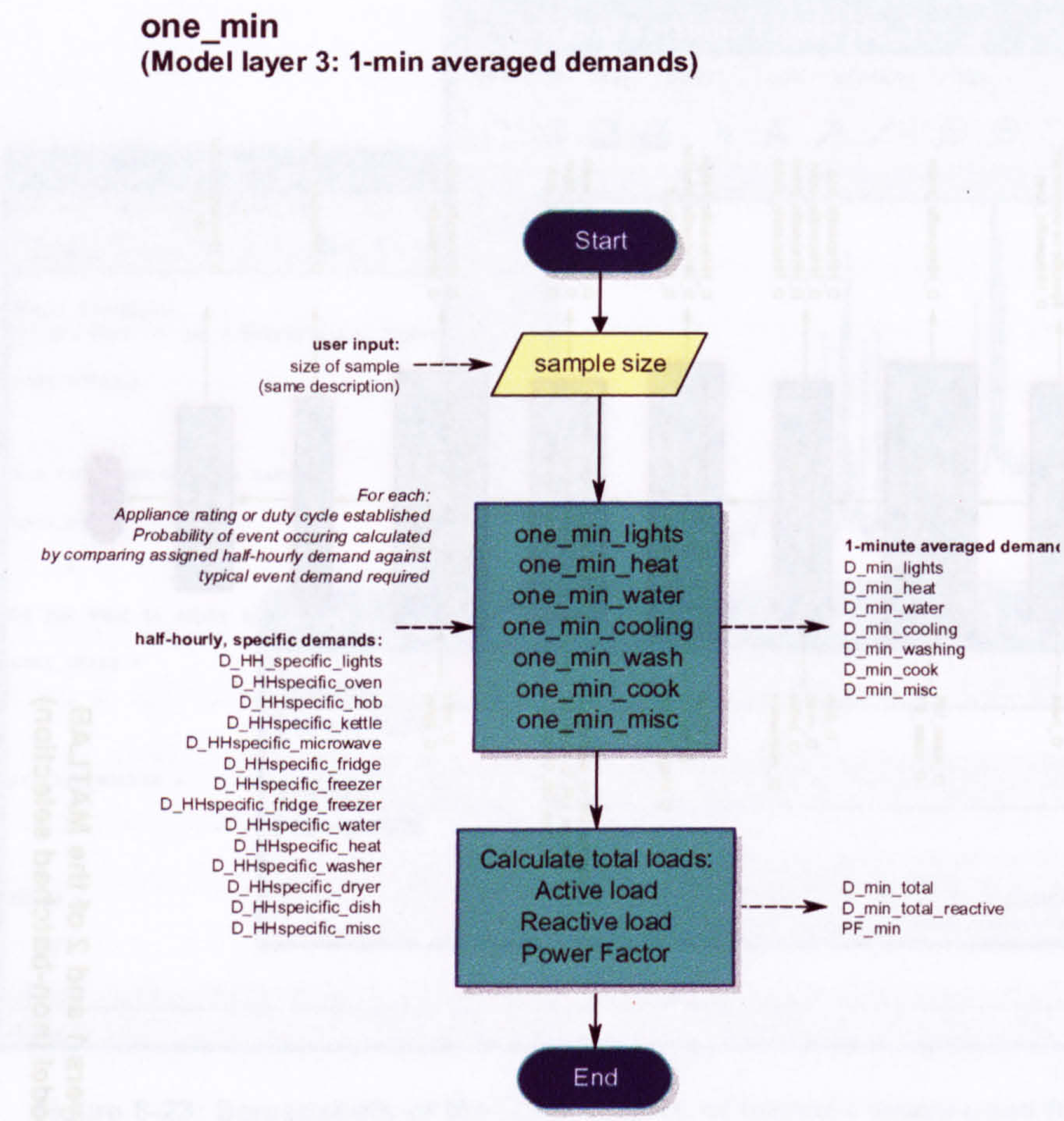


Figure 8-26: Flow chart for Layer 3 of the MATLAB version of the domestic load model (non-batched selection)

8.6.2 Speed of operation

Using this MATLAB version of the model, the time to generate a year of half-hourly demand data for a single consumer is less than 5 seconds and under 5 minutes for 500 consumers. To calculate the 1-minute demands for a single domestic consumer on a given day took less than 3 seconds (approximately one second for each layer of the model). For a complete month of 1-minute data, the model took just over 2 minutes. There was insufficient operating capacity to allow the model to run for test periods of more than one month at a time. For a single day, however, it was possible to create 50 individual 1-minute demands in just 40 seconds. 1-minute demand data for a non-domestic consumer took approximately 30 seconds for a test period of one day and 3 minutes for a complete month. 1-minute PV or solar thermal output (using a model described in Appendix G) can be calculated for a complete year in less than 4 minutes.

The current version of the model in MATLAB has not been programmed for efficient operation and it is highly likely that significant improvements could be made to the code and if other programming languages were chosen. However, these trials show that the model is workable for communities of domestic and non-domestic consumers on the scale of those supplied by a single feeder on a low voltage primary transformer, at least for individual days at the 1-minute level and for a complete year at the half-hourly.

8.6.3 Accuracy of output

The preceding sections have indicated the extent to which the models as coded in the MATLAB version compare with measured data for various specific examples. In broader terms, the model output can be compared with more generalised studies and parameter values currently used by DNOs.

Newborough and Augood's study of 30 UK homes in the late 1990s provides a range of values for daily load-factors, peak daily demands and 24-hour averaged demand values [Newborough & Augood, 1999]. These are given for the complete range (including those with electrical space heating) and the cluster for more typical homes. For comparison, the load model was used to derive similar values for 30 homes, based on random assignments of parameter values and appliance ownership on the 4 equinox dates in 1997 (Table 8-3). The sample for the load model could potentially include a wide mix of dwellings and occupants that could be more or less diverse than that of Newborough and Augood's.

The model output falls within the range of measured load factors. The model appears to underestimate the extreme peak demands, although demands for a more typical sample (i.e. without space heating) are very similar. The model also tends to assign very low peak and average demands to some homes compared to the measured data. This can be very realistic since, within an LV network area, there are likely to some unoccupied premises. The daily mean demands are slightly higher for the modelled sample compared to those in Newborough and Augood's, although the latter values (0.3-1.0 kW) seem particularly low.

Parameter	Load model output	Newborough & Augood study
Load Factor: Complete range Typical range (no space heating)	 6 – 33 % 7 – 15 %	 6 – 43 % 8 – 15 %
Peak daily demand Complete range Typical range	 0.1 – 10 kW 0.2 – 7 kW	 0.6 – 15 kW 4 – 7 kW
Mean 24-hour demand Complete range no space heating	 0.1 – 1.9 kW 0.1 – 1.3 kW	 0.3 – 1.0 kW

Table 8-3: Comparison of model output against a study of demand in 30 homes [Newborough & Augood, 1999]

Based on the survey of DNOs (Appendix A), the load model was also compared against the figures for ADMD currently used for typical spot loading. DNOs reported use of values between 1.8 – 2.3 kW per consumer for 25 homes (using gas for heating, 3-bedroom, new-build, unrestricted tariff) and 1.5 – 2.3 kW per consumer for 100 homes. The load model, applying a similar description (for ten separate runs on the 21st December, 2005), produced values between 1.8 – 2.6 kW and 1.5 – 2.2 kW accordingly.

This suggests that the load models can provide an accurate estimate within around 10% of the values currently adopted for ADMD for small groups of domestic consumers and under 5% for larger communities. The model also gives sensible values and ranges for the load factors and mean demands.

8.7 Summary of chapter 8

The comparisons made in the preceding section show that the models are capable of providing realistic electrical loads for different consumers. The test cases also illustrate some of the complexities of describing the electrical loading on networks and some of the problems relating to load measurements.

When end-use and appliance ownership are known and details of occupants are available, the domestic model is able to provide a highly accurate picture of the energy consumption for a community. The first domestic dataset concerned a group of single elderly occupants, relatively far from the average case. The model provided realistic scales and patterns of demands. The estimation of peak demands for individual consumers could be further improved by introducing a specific module for demand arising from electric showers. Such improvements would require sampling of shower demand (ideally at the 1-minute level) in a group of 50 or more homes together with an understanding of use patterns and influences.

In situations where no information is available regarding the occupants and appliance use, the domestic model must apply random assignments and will operate best when the group of homes is close to the national average or contains a broad mix of households. The second test case appeared to relate to large affluent homes and the comparison against the model output is considerably improved by assigning factors (occupant and size of home) that reflect this. A more sophisticated representation of storage heating demands, more random assignment of appliance ratings for some of the end-uses and a greater range of appliances represented in the duty cycles for miscellaneous demand might improve the model performance still further.

The non-domestic model could only be tested at the half-hourly level, for selected schools and for a large office block. The scale and patterns of the demand were in all cases realistic. The model provides a sensible representation of the daily and annual patterns, especially considering that only the annual electricity consumption and dates for the test run were required as inputs. It would be necessary to gather data for a wide range of consumers as 1-minute averaged demands in order to gain total confidence in applying the load models to non-domestic situations.

Compared to more generalised studies of demand and the values adopted for ADMD, the load models perform very well, especially for larger groups. The ADMD is estimated to be accurate within 5-10%. The results of these comparisons offer evidence that the load models are likely to provide an adequate representation of the electricity demand in the context of a typical urban LV network. Comparisons of the model output against other groups of more diverse samples of consumers, especially at the 1-minute averaged level, would strengthen confidence in the results. The next chapter examines the intended application for the load models and illustrates that, when they are used within the power flow analysis package, the predictions of the electrical performance of the network match well with measured data. Other potential applications for the models are also examined.

Chapter

9

Model Applications

I do not think that the wireless waves
that I have discovered
will have any practical application
Heinrich Rudolf Hertz

The demand models described in the earlier chapters were designed to serve the perceived needs of researchers in the field. Their relevance lies not only in the realistic representation of the electrical demands but also in the ways in which they may be usefully applied. This chapter briefly examines some of these potential applications. The models have primarily been designed to provide the electrical loading on an urban LV network, within the scope of the Solar City project. The first part of this chapter explores this setting in more detail. This is followed by a description of further ideas, for which the models have been or could be applied.

9.1 Solar City application – SEnTIENT

The Solar City project was intended to support DNOs and local authorities in examining the effect on the LV urban networks of differing levels of solar technology uptake. One of the key deliverables from the project is the Solar Energy Technology: Impact on Electricity Networks Tool (SEnTIENT) [Stokes et al, 2003]. At the heart of SEnTIENT is a GIS interface that allows users to visualise elements of the LV network. A dynamically linked database provides access to the detailed information on components such as the connecting lines and nodes, switching points and transformers. Similarly, information on the consumers, based around discrete Address Points, can be accessed via the GIS to view their assigned attributes such as category (domestic or business activity for non-domestic consumers), floor area, and occupancy or lifestyle indices. The dynamic link between the GIS interface and the underlying database allows the user to switch between various map-based views and tables of data, making access much easier. Highlighting an entry of a database table might, for example, centre on the associated map location. The GIS application also provides a link between the various components of the software package (Figure 9-1).

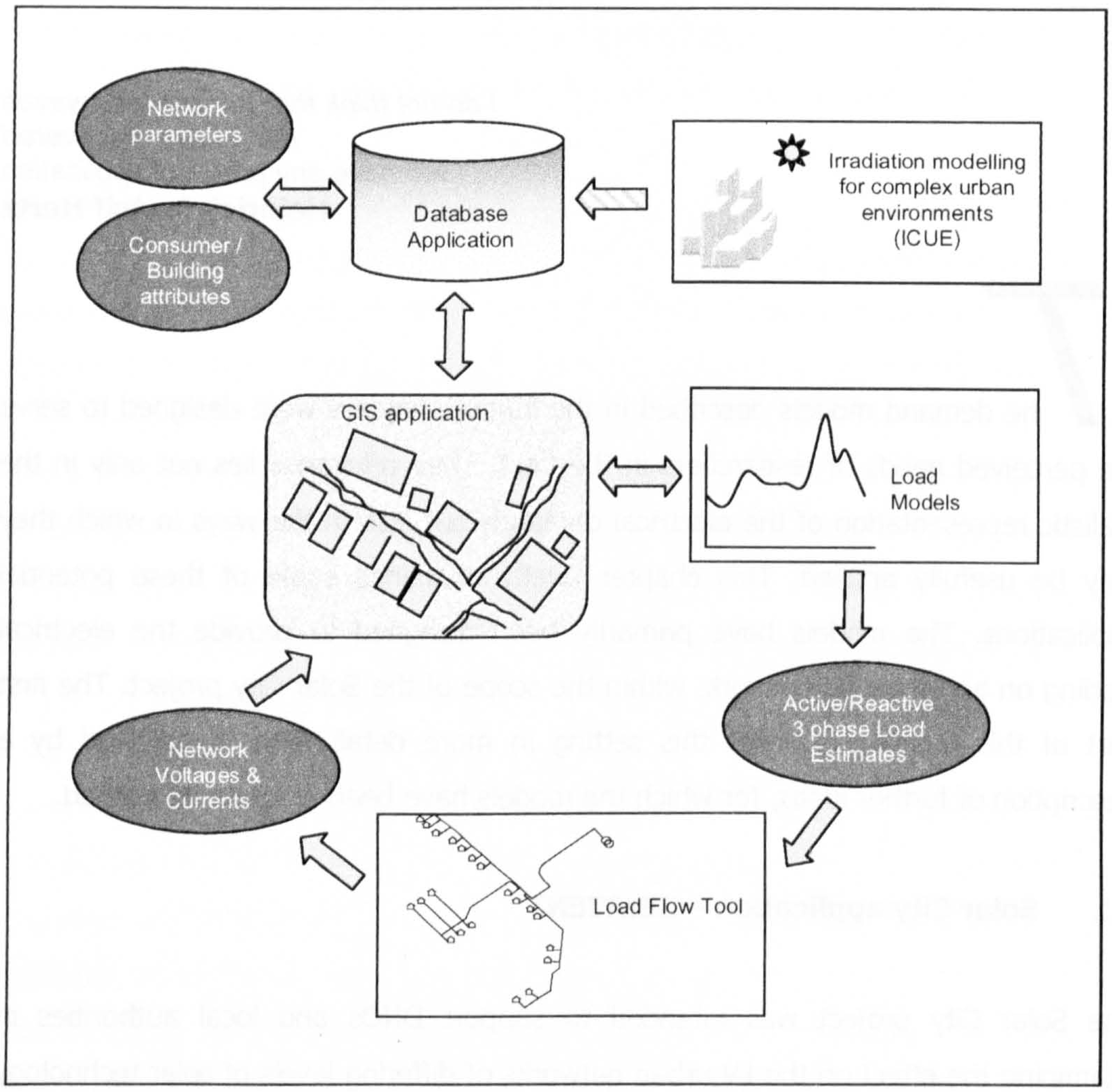


Figure 9-1: Schematic view of SEnTIENT illustrating the component modules

The load flow tool [Thomson et al, 2003] has been developed to provide a 'snap-shot' analysis of the network performance, providing voltages and currents at points in the LV network for each of the three phases. Such analysis is common in the HV and MV networks but relatively rare for the more complicated and detailed LV circuits. SEnTIENT is designed to allow the user to query the network performance, providing reports of peak and average voltages and durations for out-of-limit operation. The GIS interface facilitates visualisation of the problem areas with direct access to the underlying component descriptions, which the user may vary to repeat the analysis.

The ICUE package [Mardaljevic & Rylatt, 2000] creates irradiation values for roof surfaces, aggregated over a year on a per-pixel basis. SEnTIENT then provides a scrollable false colour image that allows users to select appropriate sites and sizes for solar panels. ICUE outputs either detailed estimates of the solar irradiation falling on the panel or, in the case of large numbers of very similar domestic buildings, exemplars for a limited range of orientations. The plan view of the selected building on the coloured image is linked to a footprint on the digital map. The irradiation values are then provided as an input to the load models, to offset the demand, in the case of PV panels, or to reduce the water heating demand in the case of solar thermal panels for domestic hot water (an alternative, simplified model for estimating 1-minute irradiation, the output from PV and solar thermal panels and the relative impact on demands from the load models is described in Appendix G).

It is within this setting that the load models have been designed to operate. The GIS interface provides the models with details about the consumers and the associated buildings at each Address Point. The active and reactive loads for each consumer connection, based on 1-minute averaged demands, are an input to the load flow tool. When the load models are used for their intended purpose – to provide the distributed load over the feeder from a primary transformer within the test case area in the centre of the city of Leicester, UK - the distribution (mean and standard deviation) of the predicted voltages at individual nodes in the network agree very well with measured data (Figure 9-2) [Rylatt et al, 2005]. Different scenarios, relating to moderate and high levels of uptake of solar panels within the city centre, are expected to yield design guidelines for DNOs for successfully handling embedded generation in urban LV networks.

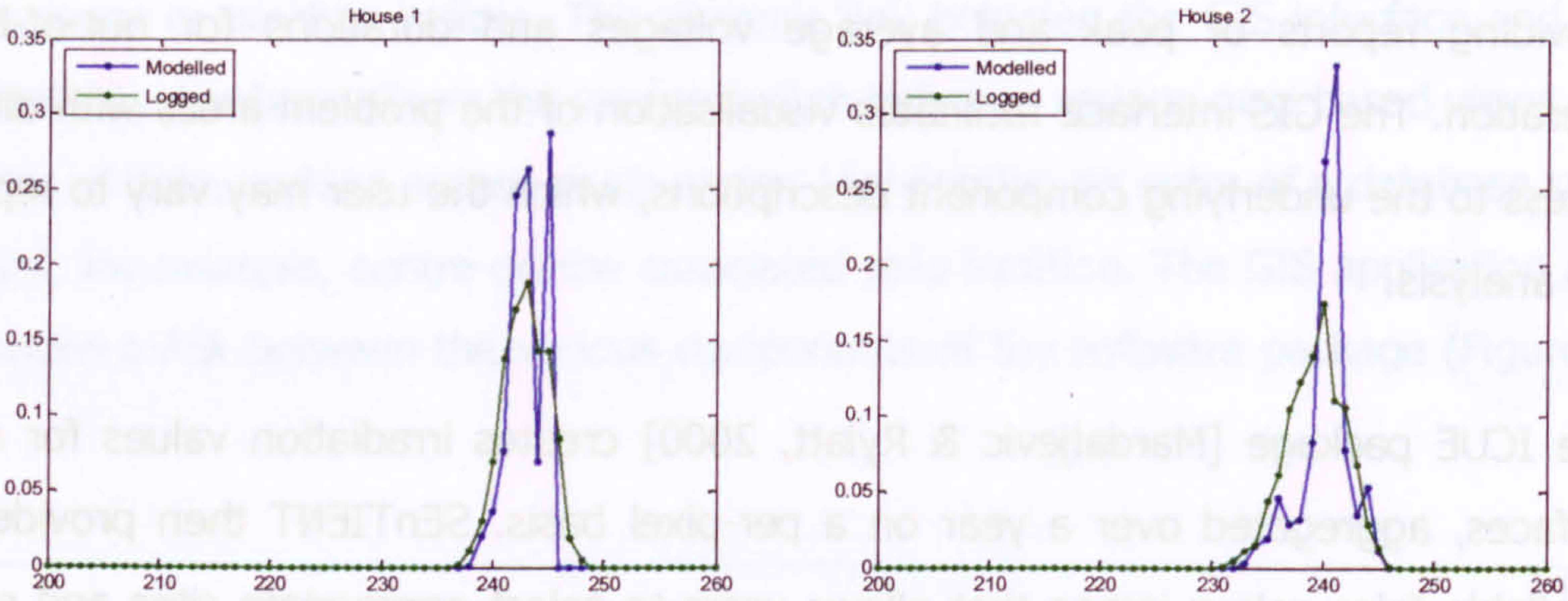


Figure 9- 2: Comparison of probability distributions of measured and modelled voltages for two houses in the Solar City test case (modelled values derived from SEnTIENT tools)

9.2 Further applications

9.2.1 Investigating energy-saving strategies

The load models could potentially support a wide range of different applications. For example, the domestic model could provide a basis for exploring different energy saving strategies such as low energy lighting and appliances and use of PV. To illustrate this potential, the model was applied to a 4-person detached house, assigned a number of electrical appliances for cooking, washing and refrigeration, during October, 2004. The model was used to make comparisons between the standard case and adjusted estimates of demand using various energy saving appliances and finally a PV panel (Table 9-1).

If all the energy saving strategies are adopted, the model estimates a total energy saving during October of around 37%, of which 27% arises from the use of efficient appliances. Comparisons such as these are possible with far simpler assumptions and models. However, the domestic model is also able to estimate the effect on peak demand, since it incorporates patterns of use. The model suggests that the peak demand can be reduced by 33%, the majority of which arises from the use of an A-rated washer, dryer and dishwasher, since these tend to be used at similar times of the day.

Test case description	Monthly energy demand (kWh)	Peak demand (kW, 1-min)	Mean demand (kW, 1-min)	Minimum demand (kW, 1-min)	Mean Daily load factor (%)
Baseline	510	8.00	0.69	0.01	13.3
+ low energy lighting	507	8.00	0.68	0.01	13.3
+ A-rated oven	493	8.00	0.66	0.01	13.6
+ A-rated washer	478	7.64	0.64	0.01	13.6
+ A-rated dryer	415	6.47	0.56	0.01	13.2
+ A-rated dishwasher	408	5.48	0.55	0.01	13.1
+ A-rated fridge-freezer	383	5.41	0.52	0.01	12.4
+ switching off standby loads	372	5.39	0.50	0.00	12.1
+ 10m^2 PV	322	5.28	0.43	-2.55[1]	10.7

Table 9-1: Comparison of the incremental effect of various energy saving strategies estimated by the domestic load model (01-10-04 to 31-10-04, 4-person, pre-war detached house, ACORN category 'B', assigned electric hob, oven, microwave, kettle, washer, dryer, dishwasher, fridge-freezer)

Since some strategies will affect the daily peak in demand whilst others have more effect on the mean demand, the model is able to show how the load factor varies. Using A-rated ovens and washing machines tends to slightly increase the load factor (13.3 to 13.6%) whilst using an A-rated fridge-freezer and removing stand-by demands would cause a reduction (13.6 to 12.1%) . Using PV, which reduces the load during mid-day, helps to even out the demand even further (12.1 to 10.7%). The model estimates the relative changes in the daily demand profile (Figure 9-3) and could be used to explore different homes and combinations of strategies.

[1] This level of export is unlikely to cause problems within the network for an individual consumer (the connections are likely to be sized to cope with around 10kW whether import or export). However, if several consumers were all exporting at this level within the network, there is a concern that, as the demand falls, the voltage at the end of long feeders could increase to above the regulated level.

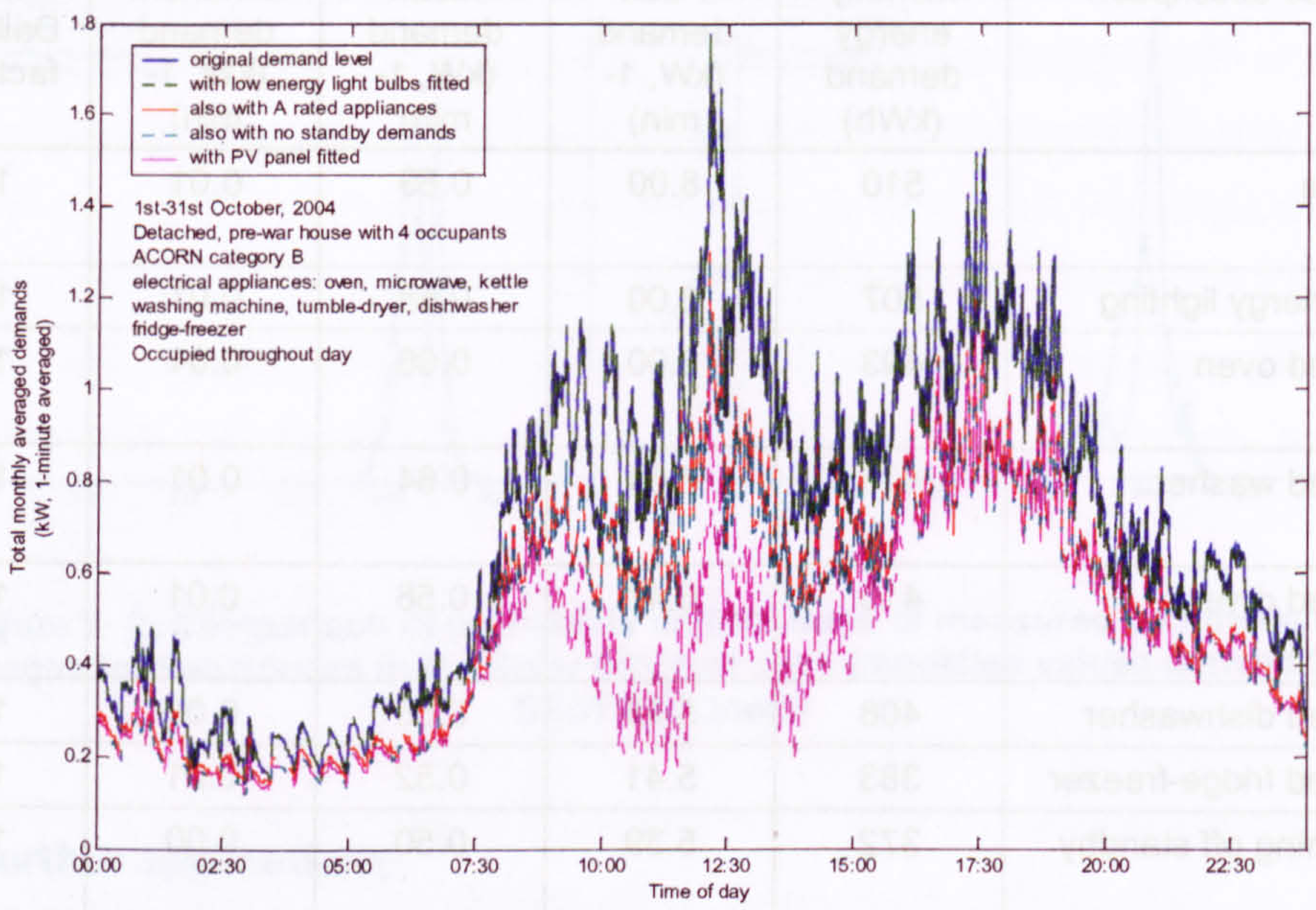


Figure 9-3: Comparison of monthly averaged total demand estimated by the model for various energy saving strategies (test details as for Table 9-1)

The model could be further adapted to simulate the effect of avoiding use of certain appliances (particularly washing machines, dryers and dishwashers) unless sufficient PV supply was available. This could identify how frequently events were delayed or interrupted to gauge the likely effect on the occupants.

9.2.2 Investigating power factors

Because the load models have an appliance/end-use basis, they may be used to investigate power factors. Typically the power factor, at a primary transformer feeder has a value around 0.96. Non-domestic consumers are incentivised by tariffs to operate near the agreed demand limit and usually aim to run as close to a unity power factor as possible. This is not the case for domestic consumers who have no financial need to adjust the power factor of the load, which, if comprising largely of refrigeration appliances, can give values as low as 0.6 [Wright, 2004].

To investigate this further, the model was used for a detached family home with a number of electrical cooking, cooling and washing appliances. Over a year, the model estimates a mean power factor of 0.97 (based on a 1-minute averaged demand) with a lowest monthly mean of 0.96 in August. The range of values was 0.67-1.00 for a year (Figure 9-4). Around 10% of the 1-minute values were less than 0.90 and 20% below 0.95 (Figure 9-5). Including an occupancy profile in the model, which set the demand between 08:00 and 17:00 equal to the cooling demand, had little effect on the August mean value.

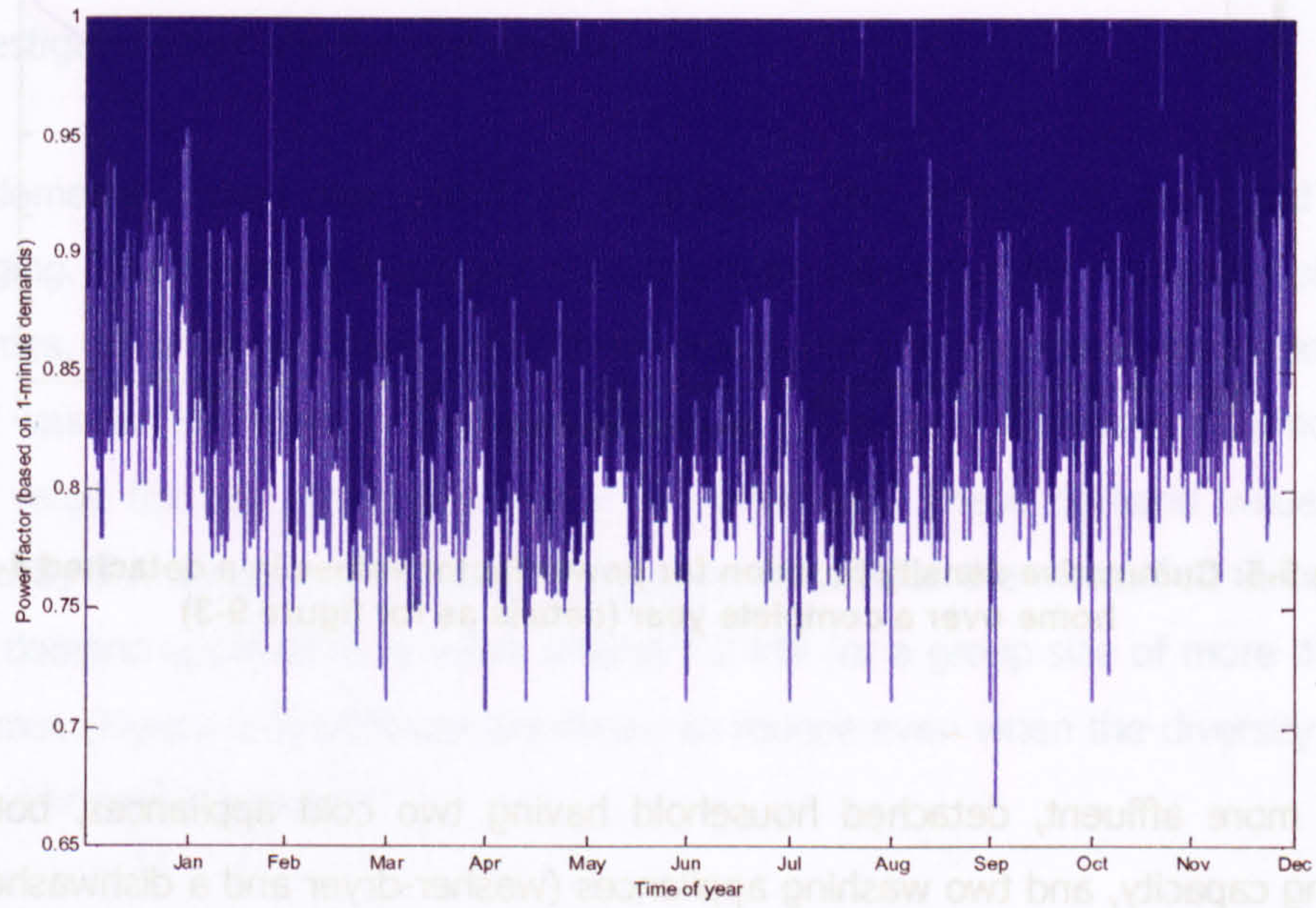


Figure 9-4: Modelled power factor values for a complete year in a family home (01-01-04 to 31-12-04, 4 occupants, pre-war detached home, ACORN category B , with electric hob, oven microwave, kettle, fridge-freezer, freezer and washer-dryer)

When the model was used to investigate the power factor for a single occupant in a small bungalow with very few electrical appliances (only a fridge-freezer and kettle were assigned), the resultant mean power factor for August was 0.98, with an annual range of 0.75 to 1.00. For relatively small households, the demand is often dominated by lighting and miscellaneous appliances, which tend to be resistive loads and have a unity power factor.

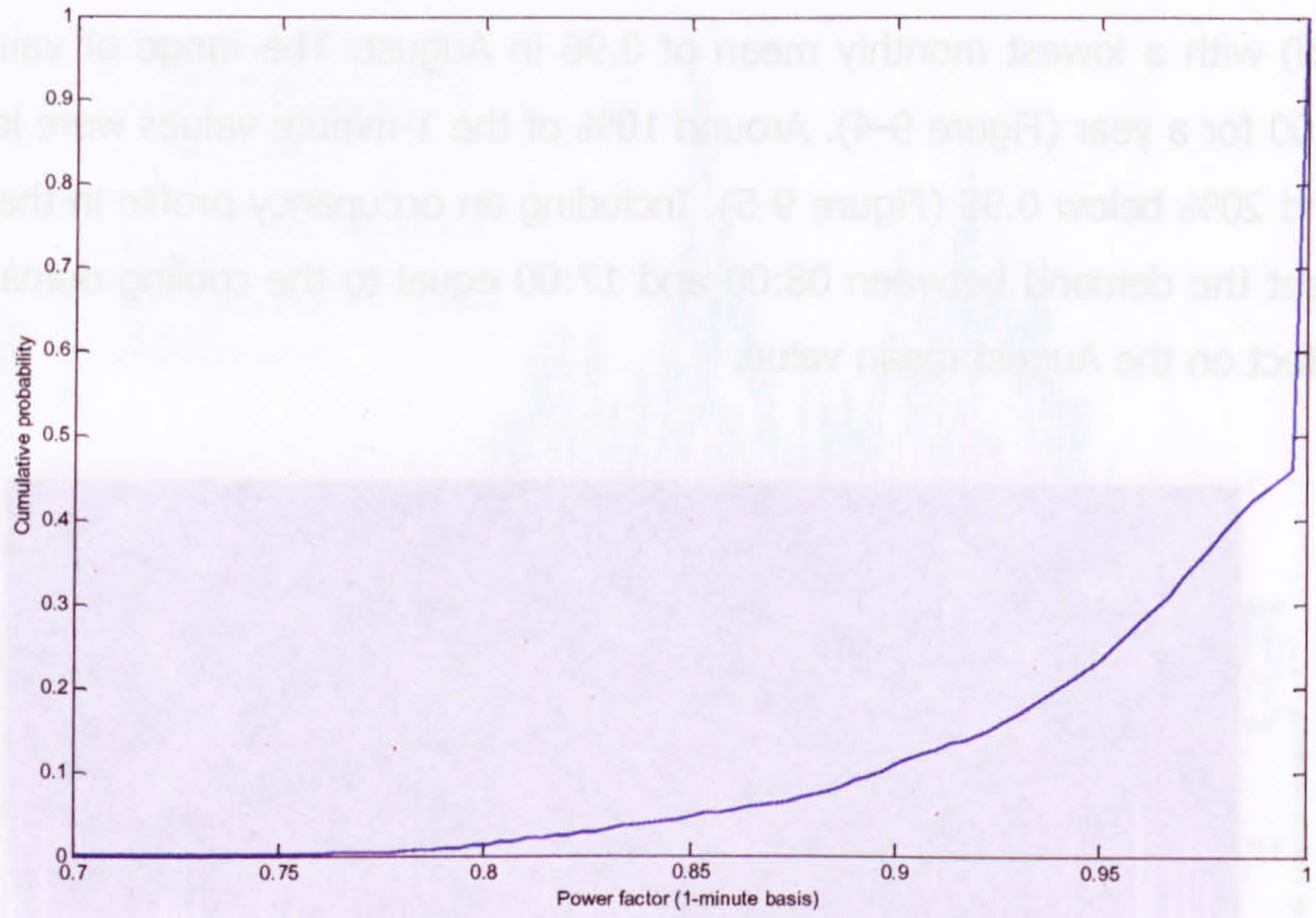


Figure 9-5: Cumulative density function for power factor values in a detached 4-person home over a complete year (details as for figure 9-3)

For a more affluent, detached household having two cold appliances, both with freezing capacity, and two washing appliances (washer-dryer and a dishwasher), the model estimates a mean August value of 0.95. In this case, inductive demands represent a more significant part of the total. If the house is considered to be vacant on a single day in August, with the entire demand arising from refrigeration, the model estimates that the mean power factor can fall as low as 0.86. Clearly in residential areas that are occupied by consumers sharing similar work/vacation patterns this might be significant to the operation of the LV networks. The load models could be used to explore different combinations of homes, their occupation and the effect of mixing residential and commercial businesses, in terms of power factor and the associated line losses due to the increased current from the reactive load.

9.2.3 Investigating time-based averaging and group size

Determining a suitable time-base for measuring and modelling is an important decision when studying electrical demand and requires a compromise between accuracy versus capacity required for handling the data. Diversity is an issue that affects the choice. If a kettle event occurs in a single home, the event will last just a few minutes. Using a time-base of longer than 1 minute is likely to give a much lower peak value for the associated demand (a 2kW event lasting 2 minutes has a demand level of just 0.13 kW on a half-hourly basis). This is less of a problem when analysing the diversified demand of large groups of consumers (few homes are likely to create a kettle event at exactly the same moment, unless related to a particular occasion, such as the end of a popular programme on TV). Since averaging is a balance between the size of a grouped community and the time-base, there is value in investigating how the two are related.

The domestic model was used to investigate the effects of time and group averaging. The 1-minute averaged demands were calculated for increasing numbers of homes, all with the same appliance assignments and occupant description. The model was run ten times for each group size, to generate a minimum, maximum and mean value for the group demand on a single day. These demand values were divided by the number of homes in the group to provide the diversified values. The mean demand approaches a value around 1.2 kW for a group size of more than 35-40 homes (Figure 9-6) although continues to reduce even when the diversity of 100 or more homes is included.

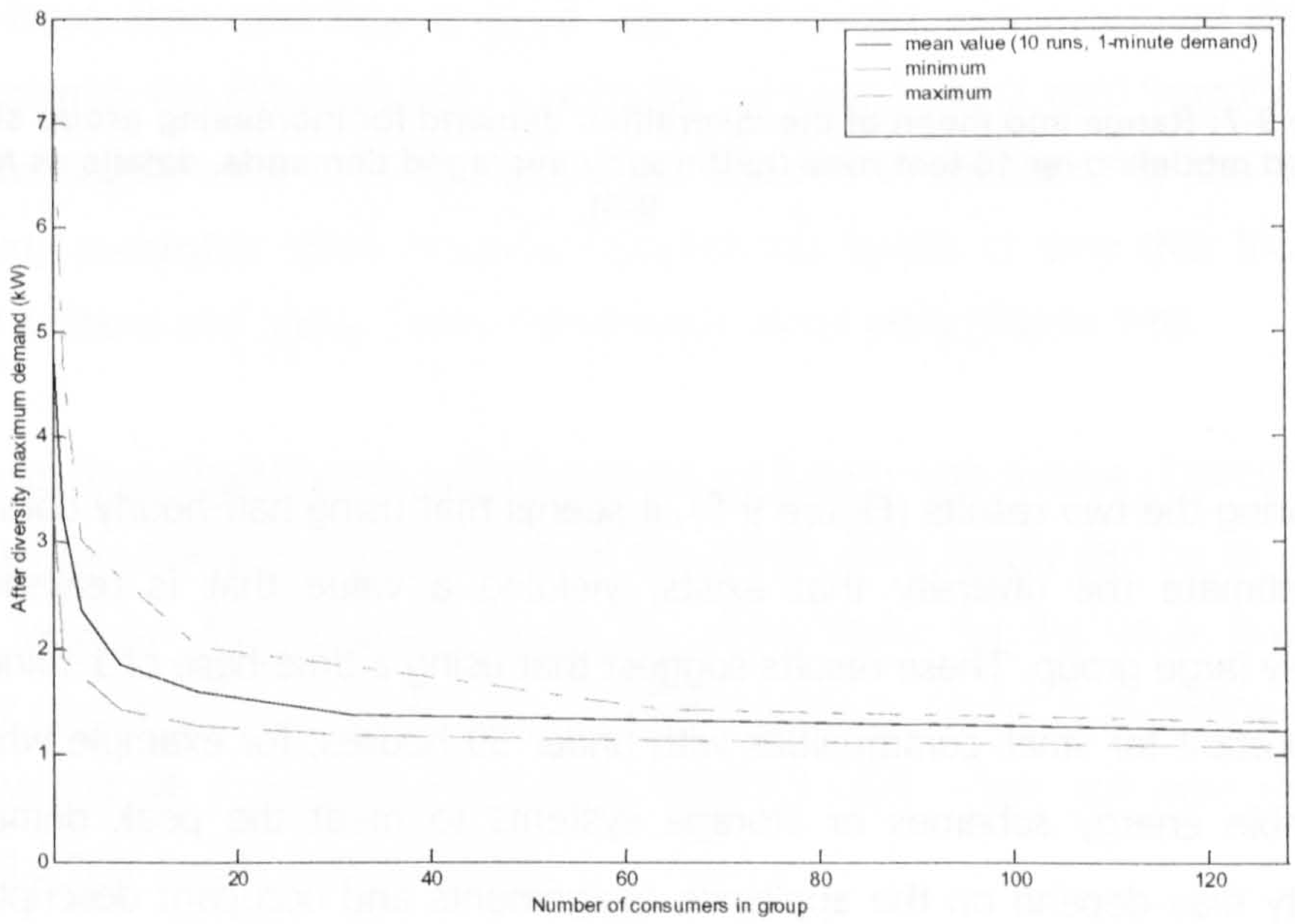


Figure 9-6: Range and mean of the diversified demand for increasing group size using the load models over 10 test runs (1-minute averaged demands, 3rd July, 2003; 1980s semi-detached house with 2 occupants, ACORN category 'C' with hob, oven microwave, kettle, washer, dryer, dishwasher and fridge-freezer)

The same exercise was repeated using half-hourly demand calculations (Figure 9-7). In this case, the diversified demand reached a steady value of around 1.1 kW for a group size of over 10 homes.

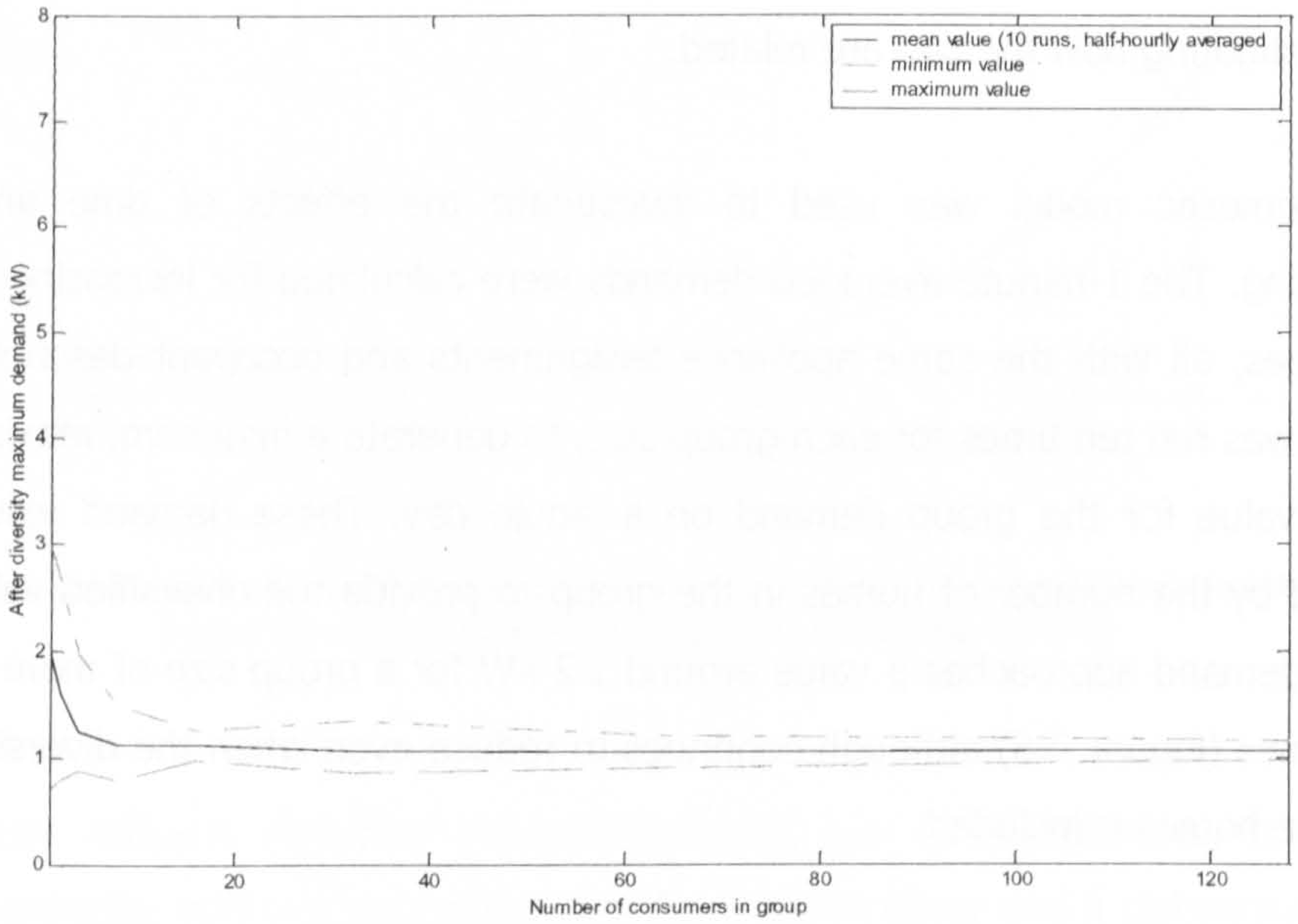


Figure 9-7: Range and mean of the diversified demand for increasing group size using the load models over 10 test runs (half-hourly averaged demands, details as for Figure 9-5)

Comparing the two results (Figure 9-8), it seems that using half-hourly data tends to over-estimate the diversity that exists, yielding a value that is realistic for an infinitely large group. These results suggest that using a time-base of 1-minute could be important for small communities with under 50 houses, for example when sizing renewable energy schemes or storage systems to meet the peak demand. The diversity may depend on the appliance assignments and occupant descriptions and the domestic model can be used to investigate a variety of different groupings to identify the time-base/group size relationship.

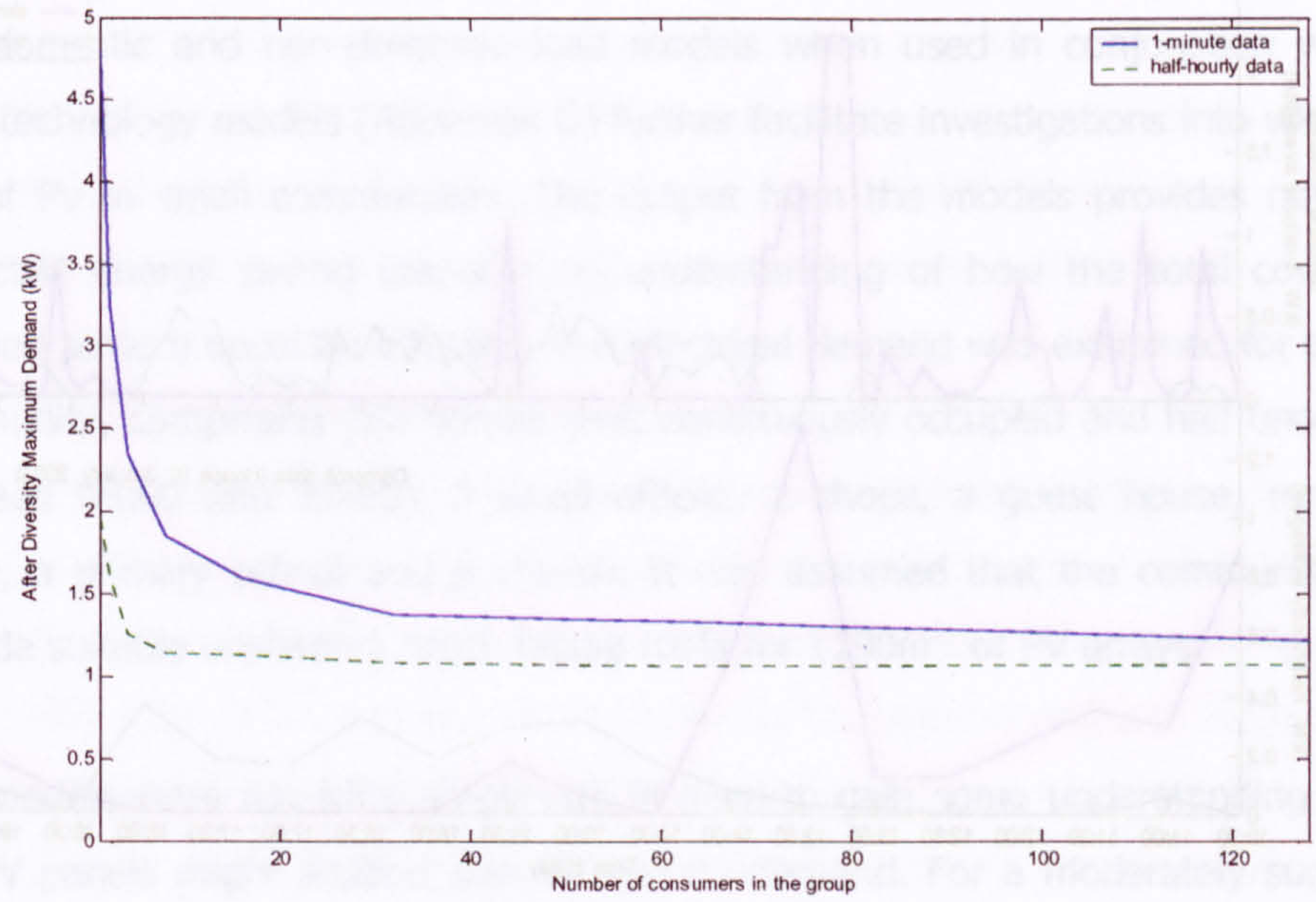


Figure 9-8: : Comparison of the diversified mean of 1-minute and half-hourly averaged demands with increasing group size (details of test as for Figures 9-5 and 9-6)

When investigating community renewable energy schemes, where it is a condition that the generated electricity is not to be exported (such as for off-grid communities), then time base is again important. In this case measured data were used to identify the effect of time base on the estimated useful yield from PV panels, where the supply could only be used when equalled or exceeded by the demand. Half-hourly averaging tends to under-estimate the length of time that the supply exceeds demand and hence over-estimates the useful yield (Figure 9-9).

The results for a single home and for a group of twenty-two homes (Tables 9-2 and 9-3) show the difference in estimates of the useful daily supply can be as much as 8% too large for the group and nearly five times larger for the single home. The domestic load and PV supply models might therefore be useful in providing a better understanding of community renewable schemes when there are only measured data at the half-hourly level available.

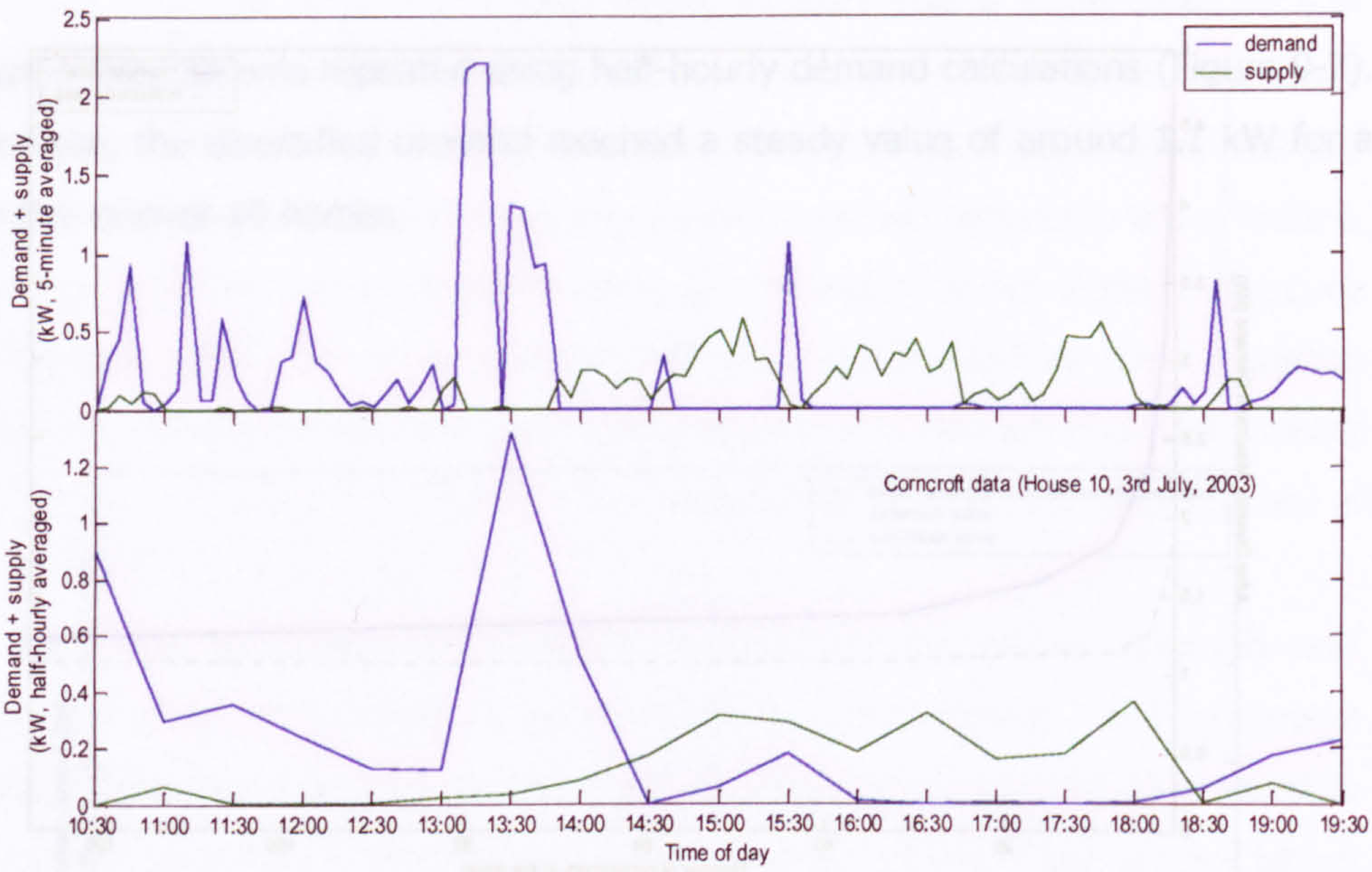


Figure 9-9: Measured PV supply and electrical demand for a single dwelling, comparing 5-minute averages with half-hourly averaged data (measured data, 3rd July, 2003)

Basis for time averaging	Useful yield (kWh)	Net demand (kWh)
5	0.047	6.939
10	0.152	6.834
15	0.169	6.817
20	0.200	6.786
25	0.252	6.734
30	0.270	6.716

Table 9-2: Comparison of time bases for estimating useful yield from PV panels (single home, 3rd July, 2003, using measured data)

Basis for time averaging	Useful yield (kWh)	Net demand (kWh)
5	20.55	92.00
10	21.21	91.34
15	21.89	90.66
20	21.49	91.06
25	24.95	87.60
30	22.11	90.44

Table 9-3: Comparison of time bases for estimating useful yield from PV panels (grouped data, 3rd July, 2003, using measured data)

9.2.4 *Investigating mixed community renewable energy schemes*

The domestic and non-domestic load models when used in conjunction with the solar technology models (Appendix G) further facilitate investigations into wide scale use of PV in small communities. The output from the models provides not just a predicted energy saving but also an understanding of how the total community demand pattern could be affected. The electrical demand was examined for a virtual community, comprising 150 homes (half continuously occupied and half unoccupied between 08:00 and 18:00), 3 small offices, 2 shops, a guest house, residential home, a primary school and a church. It was assumed that the community could provide suitable unshaded, south facing roofs for 1190m^2 of PV arrays.

The models were run for a single day in June to gain some understanding of how the PV panels might support the community demand. For a moderately sunny day the models estimate a possible saving of just over 18% of the daily energy consumption (428 kWh provided by PV[2]). The peak demand is reduced by only 8kW (153 to 145kW), since this occurs in the late evening when the available irradiation is low (figure 9-10) whilst the minimum demand falls by 14kW (22 to 8 kW). The load factor is improved by 12% (63 to 55%).

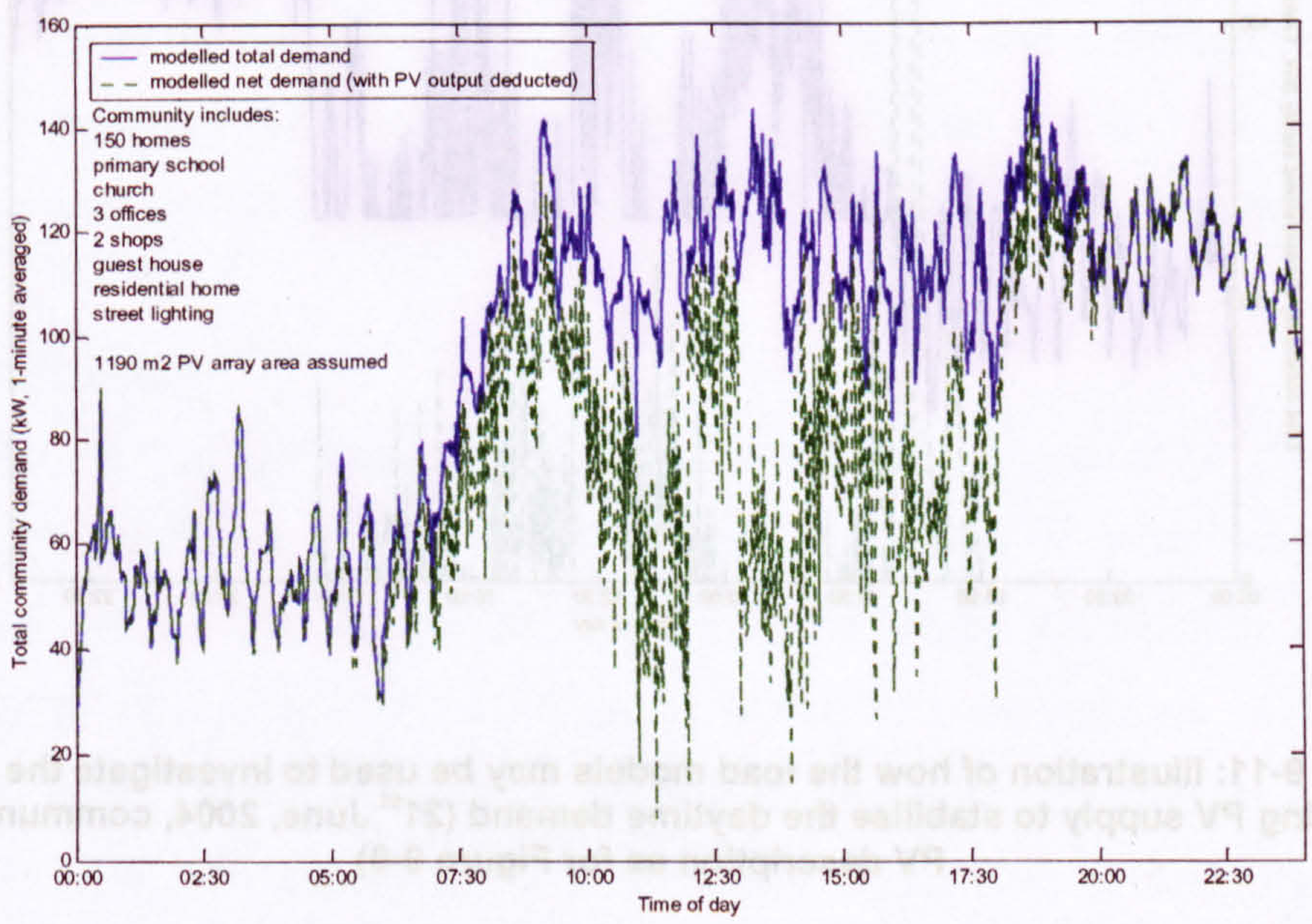


Figure 9-10: Comparison of modelled demand with and without PV supply for a mixed community of 150 homes and 9 non-domestic properties (21st June, 2004)

[2] By contrast the model estimates just 1% of the total daily energy demand is supplied from the PV arrays on a cloudy December weekday

The model results illustrate that there can be some very considerable variations in demand arising from changes in cloud cover during the day. In order to stabilise the demand, various storage and control strategies could be introduced that store the PV supply when demand falls below a pre-set level, releasing some or all of the stored supply when the demand increases. By extending the models, these storage and control mechanisms could be investigated and developed. For example, in a very crude representation of this scheme (assuming perfect storage of the supply – a very unrealistic assumption but adopted here simply to illustrate the potential application) the pre-set level was set to 65kW. This strategy would provide a relatively constant mid-day demand (Figure 9-11) which could allow improved management of additional generation within or outside the community. The control and storage strategies could be adjusted to find a reasonable compromise between the storage requirements and the additional generating capacity.

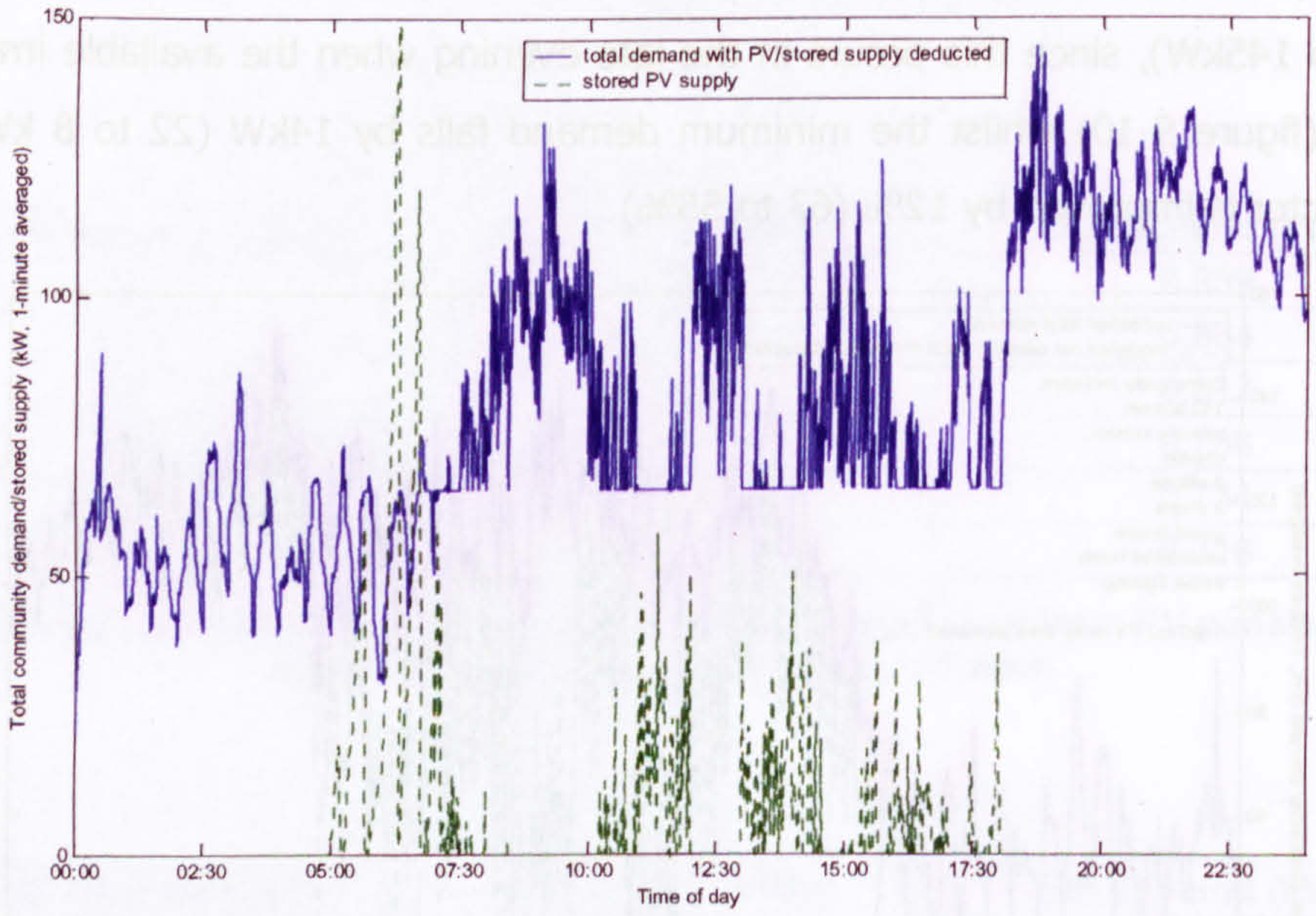


Figure 9-11: Illustration of how the load models may be used to investigate the effects of storing PV supply to stabilise the daytime demand (21st June, 2004, community and PV description as for Figure 9-9)

Clearly the load models can be used to examine the supply and demand matching for different sizes and natures of communities and the relative mix of domestic and non-domestic consumers.

9.3 Summary of chapter 9

The original environment for the load models, Solar City's SEnTIENT, provides a map-based combination of irradiation, demand and network performance estimates. This combination is intended to help support design and development of urban LV networks.

However, the models can also be usefully applied to investigate different features of the demand (power factors, time and group-based averaging) and of energy saving strategies (for individual homes and for communities) based on both reduced demand and renewable supply schemes. Some simple examples have been provided to illustrate these suggested applications.

Chapter

10

Conclusions

A final sunlight-shudder pours
away across our garden-floor
so steadily, so slow
it shows you everything you need to know
Andrew Motion

The challenge for this study has been to provide a realistic and very detailed pattern of loading on a typical urban LV electrical network. This chapter charts the most significant findings and achievements, from establishing the original objectives through development of appropriate models to demonstrating the validity of the approach. Ideas for further development of the models and opportunities to expand their usefulness are proposed. The intended contribution of the work, within a body of existing and emerging approaches to electrical demand modelling, is stated.

10.1 Conclusions

The narrowing gap between supply and demand and concerns for climate change continue to provide a driving force for increased levels of small scale embedded generation within the LV networks of the electricity distribution system. The possibility of power quality problems, in terms of over-voltages during times of maximum export and minimal loading, and the significant variability in the output from RETs were discussed and the need for new approaches to design and operation suggested.

A survey revealed that DNOs are currently using simple estimates of the group diversified peak demand as spot loads, which can lead to over-engineering and conservative designs. It has been argued that a more sophisticated description of the LV network loading used in conjunction with load flow analysis is required to facilitate a risk-based understanding of the network performance. This study was intended to provide the description of load on the LV network in order to investigate the probability of over-voltage supply and localised over-heating when PV and solar thermal panels were used intensively within an urban community (the models providing the 'as-is' loading prior to considering the load reduction for 'what-if' scenarios).

A specification was established for a load model that provides a far more detailed description of the load in spatial (per consumer) and temporal (averaged per minute) respects. A clear underlying and open basis was required to allow future development of the model and to enable application within a software package. With an increasing requirement for DNOs to manage the wasted energy associated with the reactive load, the model also needed to provide both active and reactive components and hence the power factor associated with the demand. This requires and end-use basis for the model. The focus of the research has been defined as the loading on an urban community connected to a single LV feeder of a primary transformer, thereby placing more emphasis on the domestic and lighter non-domestic consumers.

The load model has set out to provide a realistic loading. Realism has been defined as incorporating a number of measures of the characteristics of electrical load. At the outset, the load models were targeted at providing values for peak and mean demand, together with pattern descriptors such as the load factor or distribution of demand, for both individual and groups of consumers that compared well with measured values. Although intended to be used as a stand-alone model, the study has been directed at providing an input to a power flow analysis tool. The ultimate test of validity was the comparison of the aggregated loadings for a single feeder against measured values and the agreement of voltage variations at single connection points with real data. This latter work, contained within the Solar City project and applied within SEnTIENT (which have been briefly described) lay outside the scope of this thesis. However the load model output has been compared against two domestic test cases, the demands from a small number of non-domestic consumers and also research studies by others (Newborough and Augood) as well as current industry standards for ADMD.

A review of existing approaches to network loading included techniques from spot values, through demand profiling to continuously varying models, including time series analysis and neural networks. It has been shown that none of the currently available techniques and models provides all the aspects – 1-minute averaged, per consumer, domestic and light non-domestic, open end-use basis and with in-built factors to account for group diversity.

The LRG half-hourly group averaged data provided the basis for the load model that has been developed. This dataset has been described and the short-comings discussed. The data covers only domestic consumers and is highly averaged over homes in many locations. The sample sizes and test periods vary between end-use datasets. In some cases, such as for water heating and dishwashers, the sample size appears to have been small and this has been shown to compromise the performance of the derived load model. Without knowledge of the appliance ownership and end-use requirements of the sample used to make up the total demand dataset, in relation to the samples for the end-uses, it has been necessary to make assumptions to derive the miscellaneous demand and these have been outlined. Nevertheless, the LRG data claims to provide an accuracy of representation of demand, in financial terms, of 2% when viewed over a complete year and is widely used within the industry as daily profiles in the much used design tool WinDEBUT.

A three layered model for the domestic demand has been described in detail. The first layer has been described as using a sinusoidal basis, using day number as a variable. A random Gaussian component is added to the underlying trend to provide the total half-hourly group averaged demand. This was shown to be a similar approach to that used for weather parameters such as temperature and humidity. The model could be improved if this random factor were linked from one half-hour to the next and from one end-use to another (possibly achieved with smoothing). However, Layer 1 appears to give a very close representation of the underlying data and viewed on the basis of annual consumption agreed well with other research data.

The second layer of the domestic model has been described in some detail. This layer includes diversity factors based on the number of occupants, their lifestyle and income and variations in ownership of appliances and end-use requirements. In some cases (lighting and miscellaneous demands) daily profiles are varied by such factors whilst in others, the annual patterns of demand are scaled. It has been shown that such factors introduce some of the diversity that exists in demand within groups of consumers but it is necessary to use the assigned half-hourly demand as a probability to trigger appliance events in layer 3 of the model.

This third layer has been detailed, with descriptions of the appliance duty cycles that are used for comparison with the assigned demand to provide the probability. This third layer has been shown to provide a 1-minute averaged demand that introduces further elements of diversity. As far as is possible, given the paucity of measured data, the method has been justified by comparison with other studies and against the frequency of appliance use suggested by Mansouri et al [Mansouri et al, 1996].

The two domestic datasets used for evaluation were outlined. Both had their shortcomings but represented the only data available for this exercise. The first included small homes occupied mainly by single elderly people. Their consumption was, in some cases, unusually small. However, appliance ownership was known and in this case, the load model, operating at a 5-minute averaged basis, was shown to predict the total annual consumption within 0.5%. The second test case involved a group of homes for which no underlying information was available. However the data was on a 1-minute basis and was included to show how the model compares at the intended fine-grained time interval. With no knowledge of the sample and using national statistics, it was shown that the model estimates a total consumption within 22% of the measured value, although this estimate and that of the daily profiles can be much improved if it is assumed that the sample includes larger homes with a more affluent lifestyle factor.

The load model when used for a group of domestic consumers has been shown to give values within 5% for larger groups (100 homes or more) and 10% for smaller groups (25 homes) of the values for ADMD currently used by DNOs. The output also gives results that are close to Newborough & Augood's study [Newborough & Augood, 1999] in terms of the range for peak, mean and load factor values . The model has been shown to over-estimate the low level residual demand and under-estimate the extremes of individual peak demand. Further improvement may be possible with attention to modelling demand for showers as a defined appliance rather than as part of the miscellaneous demand and by studying a more detailed basis for scaling miscellaneous demand in terms of occupant factors. The model when coded in MATLAB was shown to run satisfactorily on a typical laptop PC and delivered results in a suitable time frame. It was demonstrated that a sensible batch output could be achieved for a minimal user input that defines the dates of the test period and the group size.

A non-domestic model has been described that uses layer 1 of the domestic model as a basis. This employs rescaling of the demand patterns in line with typical total and end-use consumptions measured in the NBDS [Mortimer et al, 2000] and reshaping of the daily profile using Norén's study [Norén, 1997]. The non-domestic model has been shown to give results that compare closely with measured results at the level of half-hourly averages for schools and an office. Further data is required to assess the model at the 1-minute level.

The Solar City application of the load model was presented. The model, when used to apply a distributed load over a single feeder from a primary transformer and in conjunction with a power flow analysis package, estimates voltage variation for two consumers which closely match the measured values in terms of mean and standard deviation. Further applications for the model have been described. The importance of using a fine-time scale for estimated demand for communities of less than 40 has been demonstrated. The model shows that under some circumstance power factors can fall below 0.7 and it has been demonstrated how they might be used to investigate the probability and circumstances of such occurrences. Some examples of application of the load model in conjunction with matching PV and solar thermal models have been presented for mixed communities.

Overall, the load model has been shown to match the original brief and to provide results that are realistic, in the sense that was defined earlier, when compared to available measured values. The work has been widely publicised (Appendix H) and is currently being used for research into micro combined heat and power units (mCHP). It is intended to develop the model applications further for research projects that are currently in the planning stage.

10.2 Suggestions for future developments

10.2.1 Occupancy profiles

The validation exercise of section 8.4 adopted an occupancy profile to compare the demands from the model against demand data for an unknown group of homes. This occupancy profile simply applied a gate to eliminate any demands from appliances that are likely to be controlled directly by the occupants (allowing demands only from cooling or water heating appliances during unoccupied times of weekdays). To use such profiles within the model more widely could cause two potential problems.

- People who are away during the daytime will probably trigger more events to take place whilst they are at home, in the early morning or late evening. Different demand patterns in layer 1 might be required.

- A justifiable basis is required to assign occupancy profiles (with random variations) to specific connection points.

A study to determine the typical categories of occupation and the extent to which they might apply to the UK housing stock (possibly varied by built form, income, lifestyle category, etc) would be required to implement a variety of occupancy patterns into the domestic model. The UK 2000 Time Use survey could provide a useful basis.

10.2.2 Representation of shower and other appliance demands

The comparison of modelled and measured demands presented in section 8.3 highlighted a need for a module for electric showers, in order to improve the representation of peak demand in some homes. Use of multiple shower units in homes is increasingly a problem for DNOs; contractual agreements between consumers and suppliers generally preclude the use of more than one unit.

Research is required to determine shower demand as a group-averaged pattern[1] and to identify the occupant or building factors associated with ownership and scale/patterns of use necessary for the model layer 2. Typical shower duty cycles are required for layer 3. The domestic model could be further improved by identifying similar aspects for more individual appliances and end-uses, particularly home-entertainment and computing.

10.2.3 Improvements to the representation of lighting events

The distribution of the duration of lighting events has been based on a very limited survey (section 6.7) for layer 3 of the domestic model. This survey revealed a mixture of very short duration events (as people moved between spaces) and long events (in generally occupied spaces). A more detailed survey would benefit the representation of lighting demand. Such a study could be linked to room occupation to identify how much energy is wasted in unoccupied spaces. A study of attitudes towards lighting might also determine more aspects of diversity, notably when and why lighting is used during daylight hours.

10.2.4 Improving diversity in terms of daily pattern variations

The LRG study into the effect of the built form and occupant characteristics on lighting demand facilitates the modelling of diversity in terms of scaling and demand profile. Similar studies into the relationship between the daily demand patterns and related consumer factors for a wider variety of appliances, such as washing or cooking appliances would certainly enhance the domestic model. The LRG group-averaged data show a considerable peak in mid-day cooking demand on Sundays and in the morning washing demand on Mondays. Such patterns are likely to be influenced by cultural effects related to age and by working patterns. Again, the UK2000 Time Use survey could provide a basis for this additional research.

10.2.5 Detailed studies of non-domestic demand

Clearly further research is needed into non-domestic demands to provide a more robust model. A repeat of the Swedish studies by Norén for the UK would help to identify the variations in start and finish times in various businesses and provide a basis for randomly changing the daily demand profiles. Research into the distribution

[1] The original LRG dataset included demand data for shower units but a limited sample size did not allow annual half-hourly patterns to be determined

of non-domestic appliance event characteristics (scale, duration, frequency and signature) would undoubtedly provide significant improvements to the triggering of 1-minute averaged demands in the non-domestic model.

10.3 Intended contribution of the research

In its current form, the load models have shown potential for supporting research into demand reduction and the effects of embedded generation in far more detail than before. It is being used in conjunction with a power flow analysis package [Thomson et al, 2003] to investigate the impact of PV and solar thermal panels in cities, within the Solar City project. The domestic model is also providing demand estimates for researching control mechanisms for mCHP units in homes. The ultimate goal of the research, to assist in the reduction of greenhouse gas pollution and the swing towards a more sustainable use of energy, should also be achieved in the future.

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Appendix A

User Needs Questionnaire

A.1 Introduction

Before privatisation of the UK electricity industry, there were 12 regional DNOs in England and Wales and 2 in Scotland. As a result of widespread mergers and buy-outs, there are now very few distinct companies with responsibility for the distribution network within the UK (Table A-1). As part of this research, those with responsibility for network design and operation within all of these companies were contacted (together with companies in Northern Ireland, the Channel Islands and selected LV network consultancies). Seven responses, of a possible nine, to a questionnaire were received, covering over 70% of the original network regions in England, Wales and Scotland.

The questions asked about the industry practice for representing both domestic and non-domestic loading of the LV network for design or development purposes. Included were the methods for considering load imbalance between phases and the power factor. Respondents provided information about short-term forecasting and network design tools currently used. Questions also related to their interest in renewable energy technologies and demand side management. Finally the future needs of the DNOs were examined in terms of possible tools, methodologies and models that could assist with LV network design and development in the future – with the intention of focusing current or future research to satisfy these.

Region	DNO responsible	Comments
South West England	Western Power	
South Wales		
Midlands	Central Networks	Part of e-on group Formerly Aquila
East Midlands	Central Networks	Part of e-on group Formerly EME
Merseyside and North Wales	Scottish Power - ManWeb	Part of Scottish Power (Power Systems) group
North-western England	United Utilities	
London	EDF Energy	Formerly London Energy
Eastern England	EDF Energy	Formerly linked to London Energy via 24/7 group
South-eastern England	EDF Energy	Formerly SeeBoard, linked to London Energy via 24/7 group
North-eastern England	NEDL	Combined together to form CE Electric
Yorkshire and Humberside	YEDL	
Southern England	Scottish & Southern	
Northern Scotland		
Central & Southern Scotland	Scottish Power	Part of Scottish Power (Power Systems) group

Table A-1: DNO with current LV network responsibility in England, Wales and Scotland

A.2 Survey Results

The responses to the questionnaire were provided by DNOs in confidence. The results summarise the responses without identifying the originators.

A.2.1 *Domestic consumer demand*

All respondents used an After Diversity Maximum Demand (ADMD) method of some description. Only one DNO uses a simple ADMD value for representing domestic load – all others use a combination of ADMD and unit (annual) consumptions with profiles that are provided in the network tool DEBUT[A-1] (based on the research by the Electricity Association).

In all cases, respondents reported that the domestic loading estimates were related to the size of the home (usually in terms of the number of bedrooms), fuels used (the availability and use of gas or electricity for water or space heating) and the tariff (usually a distinction between unrestricted and off-peak). For each category, two different values are generally used for day and night-time demand.

When using the simple ADMD method, a wide variety of values are used. For a group of 20 new 3-bedroomed homes using gas for space and water heating and an unrestricted tariff, peak demand estimates varied between 36 to 45kW peak demand (1.8-2.25kW per home). For 100 homes the estimates were between 148 to 225kW (1.48-2.25kW per home).

For new housing, the majority of DNOs adopt the following relationship to estimate the total loading at the transformer feeder:

$$L = a \times N + d \qquad \textbf{[A-1]}$$

where:

L = total load for the group (kW or transformer kVA)

N = number of homes in the group

a = ADMD (kW)

d = loss and diversity allowance (kW)

The values for *a* are generally based on a mixture of those available within the DEBUT model and experience of specific networks, for a variety of house sizes, tariffs and fuel usage. Varying degrees of sophistication (in terms of the granularity with which consumers were defined and the number of different values for *a*) were reported in the DNO responses. Corresponding values for the annual unit consumption are used, which provides an indication of the average demand. For

[A-1] The DEBUT tool was developed by the Electricity Association for use within the 14 UK regional DNOs, prior to privatisation, for LV network design. In 1997, the research group was the subject of a management buy-out and became a consultancy company called EA-Technology. The DEBUT tool has since been updated to operate within a Windows environment and is marketed as WinDEBUT [EA Technology, 2004] more accurate calculations, daily profiles of the half-hourly ADMD are provided within DEBUT. The value for *d* is usually taken as 8kW (one DNO uses 18kW - this may reflect different ways of accounting for line losses) although some DNOs use another value for Economy-7 consumers.

For network developments to existing housing, the DNOs have access to meter readings from the electricity suppliers to ascertain annual unit consumption (although this is disputed in one of the questionnaire responses). Although only mentioned in one response, it is thought to be common practise to record the annual maximum demand at the primary transformer LV feeder (the Maximum Demand Indicator or MDI), giving some idea of the average demand per connection.

A.2.2 *Non-domestic Demand*

Generally DNOs did not have a specific method for identifying the static loading on the LV network from non-domestic consumers. Some mentioned the profiles available in WinDEBUT for non-domestic categories. Others use experience and judgment. Developers of industrial parks may provide a typical list of appliances or this is assumed; the value of such a list is more in terms of dynamic performance of the network for predicting voltage flicker or harmonics.

One DNO reported selecting ADMD values from a list of different business categories. In practice, apart from the very large non-domestic customers, an approach similar to that for domestic consumers is usually adopted. In the case of larger non-domestic consumers, half-hourly metered data may be used or the agreed authorised supply capacity (ASC). One response mentioned adjustment of the peak demand on the basis of business activity and floor area.

More sophisticated predictions of the demand for forecasting purposes is generally reserved for the total demand at the primary transformer level – including both domestic and non-domestic consumers. Simple ADMD values or the WinDEBUT profiles tend to be used within the LV network for voltage drop calculations.

A.2.3 *Load imbalance*

The vast majority of DNOs ignore imbalance problems, especially for groups of domestic consumers. Many mentioned that an algorithm in the WinDEBUT network tool takes account of different loadings on the three phases. Significant spot loads can be applied to simulate the larger non-domestic consumers.

In the case of domestic consumers, it is general practise for site personnel to determine which phase is used for each connection, marking up the site plans accordingly. Non-domestic consumers are generally encouraged to present a balanced load across the phases but in practice unbalanced loads are not considered a problem and ignored.

Only one DNO uses a standard value (5%) for imbalance and adjusts upwards for known problem areas (single phase networks or small groups of single phase consumers).

A.2.4 *Power factors*

The approach to power factors varied widely. For domestic demand, power factors of 0.96, 0.98 or 1.0 were reported. Most DNOs use a single value for the power factor, between 0.9-1.0, regardless of consumer type, although many mentioned that this could be varied in exceptional cases.

For some, the network tools used have inbuilt standard values (of around 0.95-0.96) for the power factor, which can be overridden. For one DNO, the power factor is only considered an issue for the higher voltage networks. Another reported using measured data for specific larger non-domestic consumers.

A.2.5 *Short-term load forecasting*

None of the DNOs used short-term forecasting models for the LV network loading. Some mentioned that longer-term trends are accounted for in the mid to high-voltage networks, usually in terms of a percentage increase. The annual peak in the 11kV feeders at the primary transformers is recorded (MDI) and occasionally the trends in these values are examined. In terms of the LV network, local knowledge of generalised increase or decrease in demand may be taken into account – such as factory closures.

A.2.6 *Network design tools*

Five DNOs reported use of the WinDEBUT tool. Two used IPSA [IPSA, 2004] but only for the medium to high voltage networks. Two DNOs reported using the PSSE packages [Shaw PTI, 2004] – one of whom used this package only for 33kV with PSS-ADEPT for the LV networks. One company is using a spreadsheet model and about to commission a bespoke tool.

Less than half of the responses indicated that GIS is used. The industry standard is the SmallWorld GIS package [GE Energy, 2004] with one DNO reporting use of MIDAS GIS™ [Instrument Sales, 2003].

No specific load models are applied – the ADMD models are built into the WinDEBUT tool. One DNO applies network loads (either the ADMD value, specific spot loads or consumer metered information) within the GIS package. Another uses the WinDEBUT load models within the PSS-ADEPT package.

A.2.7 *Renewable Energy Technologies*

None of the DNO respondents felt that the inclusion of RET generators embedded in the LV network is an issue (several mentioned large-scale RET generators in the higher voltage networks as being of greater concern). In most cases, it was considered that the current low-level use of distributed RET does not present a risk to the security of supply.

However, two of the DNOs reported their research into the potential risk for security of supply should penetration increase significantly. One considers that domestic CHP is the most likely form of distributed generator that the LV networks will have to absorb and these are unlikely, on an individual basis, to generate at a higher level than the designed ADMD. The other recognises that security could be at risk if solar technologies become more cost effective and that the lack of diversity in generation would have to be considered.

Tools such as PSS-ADEPT are able to implement spot generators to simulate distributed generation and several DNOs commented on the awaited RET package that will extend the WinDEBUT capabilities [A-2].

A.2.8 *Demand by end-use*

Very few DNOs are actively involved in demand-side management. Demand by end-use is partially taken account of by the ADMD values (heating and water-heating), within the WinDEBUT network tool.

In very remote areas, one DNO reported that a programme has been started to identify causes of significant peaks. In most cases these result from simultaneous switching of off-peak space heating. The DNO in question slightly varies the off-peak start time across the region to adjust the sudden ramp in demand when storage heating is triggered. Such activity is not apparent to the consumer.

Peak demand is generally limited by the supply agreement. One DNO reports a peak domestic supply limit of 12kW. This can be exceeded when multiple shower heaters (typically 7kW peak loading) are used simultaneously. Non-domestic consumers tend to monitor and manage peaks in demand themselves. A severe financial burden can be incurred if demand exceeds the negotiated authorised supply capacity.

A.2.9 *Future needs*

The greatest area for concern appeared to be the need for a package to handle modelling of generation within the LV network and several DNOs are anticipating an extension to the existing WinDEBUT tool.

Another issue for some DNOs was the lack of a direct link between the WinDEBUT load models and their GIS representations of the network. Several new profiles are expected to operate within WinDEBUT and such links for loading the networks within the GIS by this means or directly from metered data is desirable (although some of the DNOs already achieve this).

[A-2] A product leaflet for WinDEBUT suggests that there is a version that facilitates representation of embedded generators using up to nine different profiles as spot generation on any phase. The standard profiles may be edited by the user.

The third area mentioned in some of the responses was the problems of accessing reliable data concerning the geographical layout of the LV network and the supply connections. The local networks have been developed over a period of several decades and with the accompanying variety of incompatible databases. One DNO expressed a need to gather accurate data about the existing infrastructure. However such an exercise would be beyond the resources of most companies.

Two of the responses mentioned that DNOs tend to 'fire-fight' by operating in direct response to problems. The aim is to design the LV networks with sufficient capacity to operate within the limits set by regulation with a fast response to outages, under and over-voltage situations and requests for additional loads as they arise. One DNO mentioned a wish to adopt a more pro-active response to management of the LV network by anticipating problems in advance. They required a combined load model, GIS and network design package within the next 2-4 years in order to anticipate network improvements and replacements for the UK's next electricity infrastructure review in 2010 (Ofgem's DR4 pricing and investment review).

Appendix

B

Equations and Values for Domestic Model Layer 1

(Group, half-hourly demand)

For further details of the domestic model, layer 1, refer to chapter 4.

B.1 Cooling appliances

B.1.1 Refrigerators

Half Hour No.	Daily scaling factor
1	0.941
2	0.956
3	0.911
4	0.926
5	0.916
6	0.906
7	0.888
8	0.870
9	0.870
10	0.877
11	0.853
12	0.856
13	0.865
14	0.866
15	0.903
16	0.952
17	0.966
18	0.965
19	0.970
20	0.971
21	0.966
22	0.977
23	0.981
24	0.982
25	1.006
26	1.045
27	1.074
28	1.025
29	1.033
30	1.025
31	1.030
32	1.040
33	1.055
34	1.080
35	1.133
36	1.165
37	1.172
38	1.174
39	1.168
40	1.139
41	1.113
42	1.092
43	1.096
44	1.076
45	1.078
46	1.056
47	1.009
48	0.982

Table B-1: Scaling factors for refrigerators (half-hourly, group average – based on LRG data)

Year	Typical peak demand (kW)
1970	0.092
1975	0.090
1980	0.088
1985	0.084
1990	0.078
1995	0.071
1998	0.065
2000	0.062
2005	0.054
2010	0.049
2015	0.045
2020	0.042

Table B-2: Estimated annual peak diversified demands for refrigerators (annual, half-hourly, group average – based on trends in the average annual consumption per unit [DEFRA, 2001])

B.1.2 Freezers

Half Hour No.	Sine amplitude values $s_{freezer\_HH}$	Sine constant values $k_{freezer\_HH}$	Standard deviation values $\sigma_{freezer}$
1	0.12	0.658	0.054
2	0.10	0.660	0.052
3	0.10	0.643	0.052
4	0.11	0.652	0.053
5	0.10	0.650	0.055
6	0.11	0.643	0.056
7	0.10	0.644	0.051
8	0.11	0.640	0.053
9	0.10	0.637	0.051
10	0.10	0.632	0.055
11	0.10	0.631	0.053
12	0.10	0.631	0.048
13	0.10	0.629	0.055
14	0.10	0.625	0.051
15	0.10	0.631	0.048
16	0.10	0.633	0.055
17	0.10	0.636	0.051
18	0.09	0.638	0.054
19	0.11	0.643	0.052
20	0.10	0.65	0.052
21	0.11	0.65	0.053
22	0.11	0.657	0.051
23	0.10	0.659	0.056
24	0.11	0.669	0.051
25	0.11	0.674	0.051
26	0.12	0.682	0.055
27	0.11	0.688	0.054
28	0.12	0.69	0.058
29	0.11	0.689	0.056
30	0.12	0.686	0.056
31	0.13	0.692	0.055
32	0.14	0.693	0.059
33	0.12	0.696	0.054
34	0.13	0.698	0.058
35	0.12	0.703	0.053
36	0.13	0.710	0.055
37	0.12	0.713	0.056
38	0.13	0.707	0.057
39	0.13	0.709	0.057
40	0.12	0.699	0.055
41	0.12	0.698	0.059
42	0.12	0.695	0.058
43	0.12	0.690	0.053
44	0.12	0.685	0.058
45	0.11	0.681	0.053
46	0.11	0.676	0.052
47	0.11	0.671	0.054
48	0.11	0.670	0.054

Table B-3: Factors for calculating freezer demand (half-hourly, group average – based on LRG data)

Year	Typical peak demand $p_{freezer}$ (kW)
1970	0.000[B-1]
1975	0.111
1980	0.108
1985	0.106
1990	0.104
1995	0.101
1998	0.099
2000	0.096
2005	0.089
2010	0.082
2015	0.076
2020	0.071

Table B-4: Estimated annual peak diversified demands for freezers (annual, half-hourly, group average – based on trends in the average annual consumption per unit [DEFRA, 2001])

[B-1] Freezers were relatively rare in UK homes until mid-1970s

B1.3 Fridge-freezers

Half Hour No.	Sine amplitude values s_{ff_HH}	Sine phase values φ_{ff_HH}	Sine constant values k_{ff_HH}	Standard deviation values σ_{ff}
1	0.11	2.25	0.615	0.050
2	0.10	2.25	0.618	0.049
3	0.10	2.25	0.589	0.052
4	0.10	2.39	0.603	0.049
5	0.11	2.44	0.601	0.046
6	0.11	2.42	0.597	0.047
7	0.10	2.42	0.594	0.049
8	0.11	2.45	0.589	0.048
9	0.10	2.43	0.584	0.046
10	0.10	2.43	0.582	0.049
11	0.10	2.43	0.584	0.043
12	0.10	2.49	0.581	0.046
13	0.11	2.42	0.580	0.047
14	0.11	2.45	0.584	0.048
15	0.11	2.37	0.594	0.048
16	0.11	2.35	0.604	0.048
17	0.10	2.34	0.611	0.047
18	0.11	2.39	0.610	0.047
19	0.10	2.38	0.612	0.045
20	0.10	2.35	0.615	0.047
21	0.11	2.41	0.616	0.047
22	0.11	2.37	0.617	0.051
23	0.11	2.38	0.621	0.048
24	0.11	2.34	0.631	0.053
25	0.11	2.35	0.642	0.051
26	0.11	2.28	0.657	0.052
27	0.11	2.29	0.668	0.056
28	0.11	2.28	0.659	0.056
29	0.12	2.28	0.659	0.054
30	0.12	2.28	0.657	0.056
31	0.12	2.25	0.652	0.056
32	0.12	2.28	0.660	0.055
33	0.12	2.26	0.665	0.057
34	0.13	2.27	0.670	0.055
35	0.12	2.30	0.677	0.057
36	0.12	2.25	0.686	0.055
37	0.12	2.26	0.694	0.054
38	0.12	2.24	0.688	0.056
39	0.12	2.29	0.684	0.054
40	0.12	2.30	0.673	0.053
41	0.12	2.27	0.672	0.049
42	0.11	2.36	0.663	0.051
43	0.12	2.32	0.657	0.049
44	0.11	2.31	0.654	0.053
45	0.11	2.42	0.654	0.049
46	0.12	2.40	0.651	0.052
47	0.11	2.40	0.639	0.048
48	0.11	2.36	0.625	0.048

Table B-5: Factors for calculating fridge-freezer demand (half-hourly, group average – based on LRG data)

Year	Typical peak demand p_{ff} (kW)
1970	0.000
1975	0.143
1980	0.140
1985	0.136
1990	0.133
1995	0.129
1998	0.127
2000	0.124
2005	0.114
2010	0.105
2015	0.097
2020	0.091

Table B-6: Estimated annual peak diversified demands for fridge-freezers (annual, half-hourly, group average – based on trends in the average annual consumption per unit [DEFRA, 2001])

B.2 Space Heating

Half Hour No.	Minimum values d_{heat_min}	Maximum values d_{heat_max}	Sine amplitude values s_{heat_HH}	Sine phase values φ_{heat_HH}	Sine constant values k_{heat_HH}	Standard deviation values σ_{heat}
1	0.011	0.115	0.162	5.2	0.112	0.027
2	0.111	0.683	0.430	5.3	0.483	0.050
3	0.096	0.872	0.576	5.2	0.581	0.063
4	0.041	0.906	0.639	5.2	0.549	0.065
5	0.026	0.838	0.614	5.2	0.473	0.065
6	0.019	0.789	0.598	5.2	0.416	0.071
7	0.017	0.721	0.552	5.2	0.362	0.072
8	0.017	0.669	0.490	5.2	0.323	0.073
9	0.014	0.619	0.458	5.2	0.282	0.070
10	0.017	0.549	0.436	5.2	0.242	0.067
11	0.017	0.484	0.374	5.2	0.212	0.060
12	0.020	0.432	0.320	5.2	0.194	0.050
13	0.020	0.378	0.302	5.2	0.185	0.046
14	0.020	0.348	0.250	5.2	0.169	0.037
15	0.020	0.345	0.206	5.2	0.155	0.040
16	0.001	0.161	0.131	5.3	0.059	0.018
17	0.006	0.082	0.108	5.2	0.011	0.013
18	0	0.025	0.108	5.2	0.011	0.012
19	0	0.017	0.109	5.2	0.053	0.013
20	0	0.011	0.109	5.2	0.053	0.011
21	0	0.012	0.109	5.2	0.053	0.014
22	0	0.014	0.109	5.2	0.053	0.018
23	0	0.017	0.109	5.2	0.059	0.021
24	0	0.024	0.109	5.2	0.059	0.022
25	0	0.025	0.109	5.2	0.059	0.022
26	0	0.025	0.109	5.2	0.059	0.023
27	0	0.025	0.109	5.2	0.059	0.021
28	0	0.025	0.109	5.2	0.059	0.020
29	0	0.024	0.109	5.2	0.059	0.018
30	0	0.021	0.109	5.2	0.059	0.018
31	0	0.020	0.109	5.2	0.059	0.017
32	0	0.018	0.109	5.2	0.059	0.015
33	0	0.015	0.109	5.2	0.059	0.013
34	0	0.012	0.109	5.2	0.059	0.011
35	0	0.010	0.109	5.2	0.060	0.010
36	0	0.007	0.109	5.2	0.060	0.009
37	0	0.006	0.109	5.2	0.060	0.007
38	0	0.003	0.109	5.2	0.060	0.006
39	0	0.003	0.109	5.2	0.060	0.005
40	0	0.004	0.109	5.2	0.060	0.007
41	0	0.004	0.109	5.2	0.060	0.007
42	0	0.004	0.109	5.2	0.060	0.009
43	0	0.005	0.109	5.2	0.060	0.011
44	0	0.015	0.109	5.2	0.060	0.013
45	0	0.047	0.109	5.2	0.086	0.027
46	0	0.063	0.106	5.2	0.089	0.025
47	0	0.066	0.110	5.2	0.089	0.023
48	0.120	0.260	0.107	5.2	0.072	0.023

Table B-7: Factors for calculating space heating demand (half-hourly, group average – based on LRG data)

B.3 Water Heating

Unrestricted tariff consumers:

Half Hour No.	Sine amplitude values $S_{water\ HH}$	Sine phase Values $\Phi_{water\ HH}$	Sine constant values $K_{water\ HH}$	Standard deviation values σ_{water}
1	0	-	0.041	0.058
2	0	-	0.042	0.057
3	0.002	4.0	0.041	0.056
4	0.005	3.1	0.043	0.058
5	0	-	0.040	0.053
6	0.009	3.1	0.038	0.052
7	0.004	3.1	0.034	0.052
8	0.008	3.4	0.043	0.056
9	0.005	3.4	0.043	0.055
10	0	-	0.057	0.062
11	0.088	2.6	0.112	0.118
12	0.016	1.6	0.092	0.080
13	0.021	2.2	0.112	0.109
14	0.016	1.2	0.145	0.102
15	0.008	0.1	0.115	0.107
16	0.010	5.0	0.161	0.140
17	0.019	3.7	0.129	0.135
18	0.010	3.7	0.132	0.131
19	0.014	4.5	0.113	0.121
20	0.039	4.4	0.108	0.127
21	0.041	4.2	0.094	0.127
22	0.019	4.2	0.078	0.100
23	0.003	3.7	0.063	0.079
24	0.007	2.7	0.066	0.082
25	0.021	2.7	0.064	0.089
26	0.015	2.1	0.067	0.091
27	0.011	3.2	0.063	0.079
28	0.012	2.7	0.061	0.076
29	0	-	0.063	0.082
30	0	-	0.065	0.083
31	0.013	3.4	0.059	0.073
32	0.076	2.9	0.109	0.118
33	0.037	2.8	0.092	0.105
34	0.012	2.4	0.081	0.093
35	0.032	2.1	0.080	0.097
36	0.033	2.3	0.094	0.108
37	0.041	2.2	0.108	0.113
38	0.037	2.1	0.097	0.109
39	0.034	2.2	0.081	0.107
40	0.029	2.6	0.086	0.111
41	0.033	3.1	0.083	0.106
42	0.026	2.6	0.077	0.106
43	0.010	2.6	0.061	0.082
44	0.007	3.0	0.063	0.076
45	0	-	0.059	0.076
46	0.008	3.9	0.057	0.071
47	0.010	4.6	0.051	0.070
48	0.007	4.7	0.050	0.069

Table B-8: Factors for calculating water heating demand for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

Economy-7 tariff consumers:

Half Hour No.	Sine amplitude values s_{water_HH}	Sine phase Values Φ_{water_HH}	Sine constant values K_{water_HH}	Standard deviation values σ_{water}
1	0.047	1.1	0.030	0.028
2	0.026	2.3	0.182	0.083
3	0.029	2.2	0.269	0.116
4	0.058	1.3	0.120	0.061
5	0.128	2.9	0.338	0.067
6	0.070	1.2	0.561	0.090
7	0.152	5.9	0.420	0.116
8	0.061	1.1	0.185	0.067
9	0.031	0.8	0.150	0.065
10	0.032	1.7	0.196	0.067
11	0.049	1.6	0.209	0.072
12	0.044	4.6	0.195	0.090
13	0.047	4.7	0.172	0.090
14	0.029	0.7	0.165	0.094
15	0.018	0	0.102	0.063
16	0.018	5.7	0.039	0.035
17	0.013	5.2	0.032	0.033
18	0.008	5.2	0.031	0.035
19	0.013	5.1	0.032	0.038
20	0.011	5.1	0.030	0.038
21	0.009	0.5	0.037	0.044
22	0.007	0.1	0.032	0.043
23	0.007	5.5	0.028	0.039
24	0.010	5.3	0.023	0.032
25	0.012	5.4	0.020	0.035
26	0.013	5.3	0.019	0.033
27	0.017	5.2	0.025	0.037
28	0.023	5.2	0.028	0.039
29	0.028	5.1	0.032	0.047
30	0.025	5.3	0.032	0.045
31	0.041	2.8	0.075	0.075
32	0.033	2.8	0.078	0.077
33	0	-	0.102	0.055
34	0.011	2.2	0.097	0.067
35	0.017	1.4	0.092	0.109
36	0.019	6.0	0.092	0.101
37	0.036	5.0	0.139	0.115
38	0.026	5.0	0.157	0.145
39	0.006	2.5	0.116	0.137
40	0	-	0.074	0.096
41	0	-	0.083	0.115
42	0.031	5.0	0.067	0.095
43	0.010	3.7	0.048	0.065
44	0.028	3.6	0.038	0.059
45	0.026	3.2	0.036	0.060
46	0.011	3.4	0.019	0.041
47	0	-	0.008	0.029
48	0.010	4.3	0.019	0.041

Table B-9: Factors for calculating water heating demand for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

Estimated peak annual diversified demand (kW) values, p_{water}

Year	E7	UR
1970	0.95	0.58
1975	0.99	0.60
1980	1.01	0.61
1985	1.04	0.63
1990	1.05	0.63
1995	1.08	0.65
1998	1.06	0.64
2000	1.05	0.63
2005	1.03	0.62
2010	1.02	0.62
2015	1.02	0.62
2020	1.01	0.61

Table B-10: Estimated annual peak diversified demands for water heating (annual, half-hourly, group average – based on trends in the total annual demand of an all-year round consumer [DEFRA, 2001])

B.4 Cooking demand

B4.1 Weekdays

Half Hour No.	Sine amplitude values s_{cook_HH}	Sine phase Values Φ_{cook_HH}	Sine constant values K_{cook_HH}	Standard deviation values σ_{cook}
1	0	-	0.004	0.008
2	0.003	4.6	0.004	0.011
3	0	-	0.003	0.015
4	0	-	0.002	0.005
5	0.001	4.6	0.002	0.005
6	0	-	0.002	0.004
7	0	-	0.002	0.005
8	0	-	0.002	0.005
9	0.001	4.6	0.002	0.005
10	0.001	4.2	0.002	0.004
11	0.001	4.2	0.002	0.005
12	0.004	5.7	0.005	0.007
13	0.009	5.2	0.008	0.008
14	0.007	5.9	0.009	0.012
15	0.005	6.0	0.016	0.016
16	0	-	0.046	0.028
17	0	-	0.035	0.032
18	0	-	0.039	0.037
19	0.007	3.3	0.040	0.038
20	0.006	3.4	0.040	0.039
21	0.008	4.7	0.052	0.054
22	0.005	4.3	0.060	0.057
23	0.011	4.8	0.078	0.069
24	0.026	4.1	0.164	0.099
25	0.039	4.2	0.226	0.099
26	0.028	4.8	0.232	0.113
27	0.031	4.5	0.158	0.090
28	0.046	4.0	0.095	0.076
29	0.042	3.9	0.069	0.062
30	0.039	3.9	0.064	0.062
31	0.035	4.0	0.069	0.064
32	0.039	4.0	0.093	0.074
33	0.041	4.2	0.148	0.081
34	0.031	4.1	0.228	0.106
35	0.048	5.8	0.340	0.125
36	0.022	5.4	0.261	0.121
37	0.034	6.1	0.229	0.118
38	0.003	1.3	0.182	0.098
39	0.020	3.0	0.138	0.088
40	0.019	2.9	0.083	0.066
41	0.007	2.1	0.056	0.053
42	0.004	2.9	0.034	0.038
43	0.004	1.0	0.024	0.030
44	0.005	0.0	0.021	0.028
45	0.006	6.2	0.014	0.020
46	0	-	0.009	0.014
47	0	-	0.006	0.013
48	0	-	0.007	0.018

Table B-11: Factors for calculating cooking demand on weekdays (half-hourly, group average – based on LRG data)

B4.2 Saturdays

Half Hour No.	Sine amplitude values $S_{cook\ HH}$	Sine phase Values $\Phi_{cook\ HH}$	Sine constant values $K_{cook\ HH}$	Standard deviation values σ_{cook}
1	0.004	4.1	0.009	0.013
2	0.001	4.0	0.005	0.011
3	0.003	5.7	0.004	0.008
4	0	-	0.003	0.006
5	0.007	0.5	0.004	0.015
6	0	-	0.002	0.004
7	0	-	0.006	0.016
8	0.004	5.8	0.004	0.015
9	0.002	5.8	0.002	0.005
10	0.002	5.8	0.003	0.010
11	0.003	5.8	0.004	0.008
12	0	-	0.003	0.007
13	0.003	5.9	0.003	0.009
14	0.002	5.9	0.004	0.010
15	0.005	5.9	0.012	0.014
16	0.012	5.8	0.041	0.033
17	0.013	5.2	0.056	0.032
18	0.022	3.5	0.059	0.036
19	0.010	3.5	0.060	0.050
20	0.020	3.9	0.053	0.039
21	0.024	3.5	0.068	0.062
22	0.006	0.1	0.079	0.065
23	0.006	1.0	0.104	0.073
24	0.017	3.8	0.200	0.099
25	0.023	4.7	0.266	0.097
26	0.078	5.0	0.316	0.124
27	0.046	5.2	0.200	0.083
28	0.024	4.5	0.103	0.065
29	0.054	4.7	0.066	0.053
30	0.032	4.9	0.046	0.039
31	0.028	4.1	0.049	0.048
32	0.032	4.5	0.065	0.062
33	0.045	4.3	0.147	0.081
34	0.069	4.8	0.204	0.099
35	0.065	4.9	0.277	0.117
36	0.024	4.4	0.216	0.084
37	0.057	5.0	0.209	0.108
38	0.068	5.7	0.215	0.092
39	0.019	0.0	0.200	0.107
40	0.027	0.6	0.107	0.074
41	0.023	5.6	0.056	0.055
42	0.005	5.3	0.027	0.033
43	0.006	5.1	0.016	0.022
44	0.005	5.4	0.013	0.015
45	0.007	5.8	0.023	0.028
46	0.007	4.9	0.014	0.021
47	0.004	4.6	0.010	0.018
48	0	-	0.007	0.012

Table B-12: Factors for calculating cooking demand on Saturdays (half-hourly, group average – based on LRG data)

B4.3 Sundays

Half Hour No.	Sine amplitude values s_{cook_HH}	Sine phase Values Φ_{cook_HH}	Sine constant values K_{cook_HH}	Standard deviation values σ_{cook}
1	0.005	0.8	0.004	0.016
2	0.005	4.6	0.005	0.014
3	0	-	0.003	0.008
4	0	-	0.004	0.009
5	0	-	0.002	0.004
6	0	-	0.001	0.003
7	0.005	1.6	0.005	0.018
8	0	-	0.002	0.004
9	0	-	0.001	0.002
10	0	-	0.001	0.002
11	0	-	0.003	0.006
12	0	-	0.002	0.004
13	0.002	2.5	0.003	0.005
14	0	-	0.003	0.008
15	0.007	0.7	0.011	0.015
16	0.032	6.2	0.046	0.033
17	0.004	0.5	0.071	0.061
18	0.012	2.8	0.066	0.055
19	0.005	3.2	0.100	0.071
20	0.060	3.2	0.152	0.105
21	0.133	3.6	0.241	0.090
22	0.122	3.8	0.232	0.081
23	0.154	3.7	0.299	0.095
24	0.178	4.0	0.504	0.123
25	0.148	4.5	0.585	0.144
26	0.168	4.8	0.594	0.126
27	0.081	4.9	0.386	0.145
28	0.057	5.2	0.256	0.105
29	0.033	4.8	0.157	0.080
30	0.021	5.4	0.128	0.075
31	0.040	3.4	0.138	0.078
32	0.008	4.9	0.171	0.083
33	0.017	5.1	0.213	0.082
34	0.044	4.9	0.261	0.091
35	0.068	4.4	0.266	0.128
36	0.037	4.8	0.278	0.113
37	0.004	6.2	0.245	0.121
38	0.025	0.6	0.189	0.102
39	0.020	0.9	0.144	0.089
40	0.005	2.1	0.094	0.075
41	0.016	2.7	0.049	0.051
42	0.011	1.7	0.043	0.047
43	0.007	0.5	0.022	0.027
44	0	-	0.019	0.026
45	0.015	5.4	0.016	0.019
46	0.005	4.7	0.005	0.011
47	0.009	4.5	0.009	0.017
48	0.007	4.2	0.007	0.015

Table B-13: Factors for calculating cooking demand on Sundays (half-hourly, group average – based on LRG data)

B4.4 Hobs and Ovens (p_{cook} values)

Year	Annual peak value (kW) P_{cook} for combined ovens & hobs	% demand used for hobs	% demand used for ovens
1970	1.59	27	73
1980	1.408	33	67
1990	1.002	40	60
1996	0.796	48	52
2000	0.772	51	49
2010	0.788	56	44
2020	0.780	60	40

Table B-14: Estimated annual peak diversified demands for hobs and ovens and the relative split between hobs and ovens (annual, half-hourly, group average – based on trends in the total annual demand of a all-year round consumer [DEFRA, 2001])

B4.5 Kettles(p_{cook} values)

Year	Annual peak value (kW) P_{cook} for kettles
1970	0.227
1980	0.251
1990	0.268
1996	0.252
2000	0.259
2010	0.299
2020	0.323

Table B-15: Estimated annual peak diversified demands for kettles (annual, half-hourly, group average – based on trends in the total annual demand of a all-year round consumer [DEFRA, 2001])

B4.6 Microwaves (p_{cook} values)

Year	Annual peak value (kW) P_{cook} for microwaves
1970	0
1980	0.136
1990	0.163
1996	0.159
2000	0.163
2010	0.202
2020	0.225

Table B-16: Estimated annual peak diversified demands for microwaves (annual, half-hourly, group average – based on trends in the total annual demand of a all-year round consumer [DEFRA, 2001])

B.5 Wet appliance demand

B5.1 Washing machines - Unrestricted tariff – Mondays

Half Hour No.	Sine amplitude values $s_{wet\ HH}$	Sine phase Values $\Phi_{wet\ HH}$	Sine constant values $K_{wet\ HH}$	Standard deviation values σ_{wet}
1	0.004	2.8	0.009	0.020
2	0	-	0.007	0.019
3	0.006	3.6	0.009	0.021
4	0.003	4.6	0.005	0.014
5	0.046	3.0	0.041	0.042
6	0.039	3.3	0.036	0.050
7	0.002	2.5	0.005	0.011
8	0.001	3.8	0.004	0.006
9	0.026	5.5	0.016	0.046
10	0.008	5.5	0.005	0.015
11	0.005	0.1	0.005	0.023
12	0.001	5.0	0.008	0.019
13	0.006	0.7	0.024	0.044
14	0.013	2.2	0.020	0.032
15	0.006	0.5	0.102	0.074
16	0.046	0.9	0.122	0.096
17	0.083	0.5	0.263	0.148
18	0.078	0	0.394	0.190
19	0.030	0	0.417	0.181
20	0.065	0.5	0.368	0.160
21	0.120	0.3	0.385	0.146
22	0.100	5.8	0.370	0.171
23	0.075	5.4	0.347	0.144
24	0.040	6.2	0.292	0.137
25	0.086	6.1	0.281	0.142
26	0.038	0.4	0.246	0.145
27	0.070	0.1	0.209	0.113
28	0.009	5.6	0.165	0.111
29	0.033	5.2	0.164	0.108
30	0.043	5.5	0.176	0.138
31	0.043	0.9	0.158	0.100
32	0.050	6.2	0.155	0.105
33	0.050	5.3	0.164	0.110
34	0.037	5.0	0.148	0.082
35	0.028	5.9	0.139	0.088
36	0.012	4.0	0.128	0.082
37	0.031	4.4	0.131	0.106
38	0.051	5.5	0.120	0.095
39	0.073	5.7	0.157	0.095
40	0.028	5.2	0.119	0.088
41	0.039	5.2	0.091	0.090
42	0.032	5.6	0.086	0.084
43	0.015	5.6	0.083	0.083
44	0.034	1.1	0.059	0.065
45	0.007	1.8	0.038	0.044
46	0.007	3.9	0.027	0.045
47	0.010	5.6	0.030	0.060
48	0.007	6.2	0.013	0.026

Table B-17: Factors for calculating washing machine demand on Mondays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.2 Washing machines - Unrestricted tariff – Saturdays

Half Hour No.	Sine amplitude values $s_{wet\ HH}$	Sine phase Values $\Phi_{wet\ HH}$	Sine constant values $K_{wet\ HH}$	Standard deviation values σ_{wet}
1	0.05	5.0	0.024	0.041
2	0.012	4.6	0.017	0.041
3	0.007	5.2	0.012	0.032
4	0.008	4.6	0.008	0.031
5	0.013	2.4	0.014	0.035
6	0.007	2.9	0.014	0.033
7	0	0	0.005	0.022
8	0	0	0.003	0.015
9	0	0	0.006	0.028
10	0	0	0.005	0.023
11	0	0	0.007	0.034
12	0.003	4.2	0.012	0.032
13	0.009	3.8	0.023	0.054
14	0.004	3.4	0.028	0.041
15	0.010	2.2	0.030	0.041
16	0.027	2.6	0.109	0.071
17	0.029	2.7	0.159	0.089
18	0.020	5.3	0.203	0.119
19	0.050	0.2	0.310	0.155
20	0.051	5.2	0.372	0.142
21	0.063	6.0	0.430	0.166
22	0.057	5.3	0.444	0.180
23	0.044	4.8	0.391	0.163
24	0.071	5.6	0.380	0.151
25	0.057	0.0	0.359	0.135
26	0.014	4.8	0.326	0.146
27	0.045	6.1	0.286	0.113
28	0.085	0.2	0.284	0.134
29	0.028	0.0	0.279	0.128
30	0.019	5.0	0.251	0.104
31	0.029	3.2	0.210	0.135
32	0.007	1.8	0.212	0.109
33	0.013	0.9	0.186	0.120
34	0.008	1.7	0.146	0.098
35	0.020	4.9	0.124	0.091
36	0.055	0.5	0.120	0.081
37	0.054	0.5	0.120	0.081
38	0.033	0.2	0.117	0.088
39	0.006	6.1	0.111	0.080
40	0.004	0.6	0.087	0.066
41	0.015	5.5	0.072	0.071
42	0.025	6.0	0.071	0.068
43	0.015	5.4	0.066	0.060
44	0.013	4.3	0.047	0.053
45	0	0	0.050	0.050
46	0.011	6.0	0.037	0.044
47	0	0	0.043	0.057
48	0.004	4.1	0.024	0.040

Table B-18: Factors for calculating washing machine demand on Saturdays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.3 Washing machines - Unrestricted tariff – Sundays

Half Hour No.	Sine amplitude values $s_{wet\ HH}$	Sine phase Values $\Phi_{wet\ HH}$	Sine constant values $K_{wet\ HH}$	Standard deviation values σ_{wet}
1	0.016	4.8	0.024	0.042
2	0.011	5.6	0.017	0.041
3	0.012	5.3	0.018	0.038
4	0.009	3.7	0.022	0.041
5	0.036	2.8	0.040	0.055
6	0.032	3.3	0.032	0.046
7	0.004	3.7	0.010	0.027
8	0.012	4.9	0.012	0.033
9	0.033	5.0	0.019	0.047
10	0.010	5.0	0.006	0.023
11	0.016	4.6	0.010	0.038
12	0.008	4.6	0.005	0.024
13	0.016	4.5	0.013	0.047
14	0.009	4.6	0.021	0.041
15	0.007	3.8	0.021	0.042
16	0	-	0.032	0.042
17	0.022	2.6	0.055	0.055
18	0.011	1.3	0.096	0.096
19	0.050	1.2	0.184	0.184
20	0.073	0.6	0.251	0.251
21	0.088	0.1	0.348	0.348
22	0.080	5.2	0.406	0.406
23	0.057	5.0	0.358	0.358
24	0.057	5.7	0.323	0.323
25	0.062	5.7	0.316	0.146
26	0.069	5.4	0.267	0.137
27	0.058	5.0	0.268	0.131
28	0.065	5.2	0.193	0.104
29	0.061	5.2	0.220	0.120
30	0.058	4.5	0.198	0.122
31	0.073	4.7	0.201	0.115
32	0.052	4.4	0.187	0.116
33	0.082	4.8	0.181	0.112
34	0.076	5.0	0.189	0.123
35	0.080	5.0	0.154	0.101
36	0.048	4.6	0.146	0.097
37	0.019	4.3	0.119	0.083
38	0.030	5.0	0.120	0.081
39	0.040	5.1	0.122	0.101
40	0.007	5.6	0.122	0.095
41	0.032	5.9	0.090	0.074
42	0.035	5.7	0.079	0.084
43	0.006	0.4	0.085	0.087
44	0.022	0.4	0.074	0.069
45	0.005	1.6	0.055	0.049
46	0.010	0	0.035	0.041
47	0.014	0	0.031	0.045
48	0.010	4.8	0.025	0.048

Table B-19: Factors for calculating washing machine demand on Sundays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.4 Washing machines - Unrestricted tariff – Other weekdays

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.002	1.4	0.011	0.027
2	0.001	1.4	0.005	0.018
3	0	0	0.002	0.010
4	0	0	0.001	0.006
5	0.022	2.4	0.025	0.044
6	0.010	2.6	0.016	0.038
7	0	0	0.004	0.014
8	0.003	5.0	0.003	0.007
9	0.026	5.4	0.016	0.043
10	0	0	0.004	0.014
11	0	0	0.005	0.020
12	0.005	2.9	0.020	0.039
13	0.002	4.2	0.039	0.054
14	0.004	2.8	0.032	0.041
15	0.029	0.5	0.072	0.059
16	0.013	0.9	0.081	0.071
17	0.046	1.0	0.186	0.130
18	0.029	6.2	0.262	0.148
19	0.006	2.0	0.257	0.120
20	0.023	5.9	0.279	0.133
21	0.009	0.0	0.260	0.134
22	0.029	0.0	0.239	0.134
23	0.019	5.9	0.216	0.127
24	0.014	0.5	0.180	0.117
25	0.014	4.6	0.171	0.120
26	0.009	4.4	0.164	0.126
27	0.007	5.2	0.127	0.096
28	0.022	0.0	0.116	0.099
29	0.019	5.5	0.131	0.109
30	0.009	4.9	0.116	0.089
31	0.010	5.8	0.103	0.078
32	0.015	5.4	0.108	0.086
33	0.021	6.0	0.112	0.087
34	0.010	5.5	0.127	0.099
35	0.017	6.0	0.125	0.100
36	0.018	6.2	0.123	0.094
37	0.018	6.0	0.113	0.092
38	0.025	4.9	0.114	0.096
39	0.022	5.3	0.119	0.091
40	0.010	6.0	0.098	0.082
41	0.034	6.0	0.100	0.089
42	0.023	0.5	0.094	0.082
43	0.025	0.7	0.089	0.078
44	0.018	0.4	0.080	0.086
45	0.003	2.5	0.050	0.055
46	0.002	1.9	0.036	0.049
47	0.003	0.6	0.031	0.051
48	0.002	0.4	0.016	0.031

Table B-20: Factors for calculating washing machine demand on other weekdays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.5 *Washing machines - Economy 7 tariff – Mondays*

Half Hour No.	Sine amplitude values S_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.028	5.0	0.063	0.055
2	0.011	4.0	0.035	0.049
3	0.021	3.4	0.032	0.040
4	0.053	4.0	0.058	0.060
5	0.042	4.5	0.066	0.064
6	0.028	3.8	0.113	0.075
7	0.053	5.6	0.109	0.075
8	0.118	6.2	0.148	0.112
9	0.058	5.7	0.126	0.089
10	0.046	5.5	0.088	0.072
11	0.040	6.0	0.184	0.075
12	0.071	5.5	0.130	0.095
13	0.071	6.0	0.162	0.081
14	0.061	0.4	0.185	0.090
15	0.029	4.7	0.184	0.100
16	0.019	5.2	0.259	0.125
17	0.022	0.0	0.297	0.111
18	0.032	0.7	0.282	0.136
19	0.028	6.1	0.296	0.136
20	0.024	3.9	0.317	0.128
21	0.038	3.4	0.280	0.162
22	0.016	2.3	0.260	0.124
23	0.017	5.3	0.232	0.109
24	0.017	2.5	0.195	0.126
25	0.016	4.1	0.163	0.095
26	0.012	4.8	0.157	0.103
27	0.032	4.9	0.146	0.097
28	0.049	4.7	0.134	0.095
29	0.023	4.4	0.109	0.078
30	0.049	4.0	0.103	0.088
31	0.041	4.5	0.098	0.098
32	0.047	5.0	0.083	0.070
33	0.049	4.6	0.068	0.056
34	0.024	3.3	0.067	0.082
35	0.020	4.3	0.068	0.068
36	0.030	5.2	0.061	0.055
37	0.030	4.5	0.059	0.064
38	0.018	4.9	0.050	0.055
39	0.023	5.2	0.058	0.060
40	0.026	5.1	0.061	0.057
41	0.016	4.6	0.040	0.051
42	0.007	5.4	0.029	0.036
43	0.015	5.5	0.038	0.056
44	0.016	5.0	0.029	0.048
45	0.005	5.5	0.022	0.028
46	0.015	4.7	0.034	0.039
47	0.011	0.4	0.066	0.054
48	0.006	0.2	0.087	0.043

Table B-21: Factors for calculating washing machine demand on Mondays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.6 Washing machines - Economy 7 tariff – Saturdays

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.010	1.6	0.064	0.042
2	0.027	4.8	0.055	0.056
3	0.020	5.1	0.051	0.061
4	0.054	4.1	0.045	0.057
5	0.040	4.9	0.053	0.045
6	0.022	3.2	0.111	0.074
7	0.030	5.2	0.068	0.074
8	0.073	6.1	0.118	0.094
9	0.041	5.8	0.101	0.074
10	0.003	4.2	0.071	0.066
11	0.025	6.0	0.190	0.067
12	0.046	5.1	0.119	0.072
13	0.065	5.3	0.121	0.077
14	0.047	6.0	0.117	0.071
15	0.010	4.7	0.138	0.086
16	0.008	1.0	0.164	0.089
17	0.011	0.0	0.201	0.114
18	0.045	5.2	0.197	0.109
19	0.060	5.2	0.194	0.106
20	0.006	0.2	0.245	0.112
21	0.031	4.6	0.299	0.158
22	0.070	4.7	0.316	0.138
23	0.029	5.1	0.301	0.137
24	0.067	5.0	0.242	0.113
25	0.067	4.9	0.270	0.137
26	0.069	5.0	0.189	0.105
27	0.063	4.5	0.166	0.096
28	0.078	4.5	0.163	0.113
29	0.053	4.3	0.131	0.092
30	0.067	4.4	0.130	0.063
31	0.020	4.9	0.110	0.070
32	0.042	4.5	0.111	0.076
33	0.025	4.0	0.079	0.062
34	0.014	5.1	0.071	0.063
35	0.022	5.4	0.069	0.080
36	0.024	4.6	0.050	0.052
37	0.013	5.8	0.043	0.041
38	0.015	4.8	0.068	0.066
39	0.021	3.9	0.076	0.063
40	0.020	3.7	0.064	0.066
41	0.018	4.4	0.049	0.058
42	0.006	3.7	0.040	0.054
43	0.017	1.4	0.035	0.048
44	0.004	2.3	0.030	0.041
45	0.014	0.0	0.034	0.045
46	0.010	5.5	0.036	0.045
47	0.014	3.5	0.041	0.044
48	0.030	4.4	0.063	0.046

Table B-22: Factors for calculating washing machine demand on Saturdays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.7 Washing machines - Economy 7 tariff – Sundays

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.021	4.5	0.044	0.044
2	0.019	3.8	0.058	0.058
3	0.022	3.6	0.056	0.056
4	0.057	4.3	0.065	0.065
5	0.040	5.1	0.062	0.062
6	0.025	3.5	0.067	0.067
7	0.039	5.1	0.062	0.062
8	0.072	6.1	0.076	0.076
9	0.035	6.2	0.064	0.064
10	0.019	5.5	0.058	0.058
11	0.019	5.9	0.069	0.069
12	0.037	5.2	0.065	0.065
13	0.045	5.5	0.081	0.077
14	0.010	5.0	0.080	0.082
15	0.015	2.6	0.084	0.077
16	0.035	0.0	0.094	0.087
17	0.065	0.4	0.158	0.076
18	0.056	6.1	0.189	0.094
19	0.036	5.6	0.152	0.069
20	0.029	5.9	0.168	0.093
21	0.016	5.0	0.214	0.122
22	0.080	5.2	0.266	0.153
23	0.074	4.9	0.224	0.103
24	0.075	4.8	0.206	0.139
25	0.050	4.2	0.211	0.130
26	0.032	5.2	0.185	0.100
27	0.050	4.9	0.157	0.106
28	0.050	4.7	0.139	0.094
29	0.025	4.2	0.105	0.088
30	0.014	5.7	0.082	0.066
31	0.009	5.3	0.092	0.076
32	0.013	5.1	0.099	0.090
33	0.038	4.9	0.080	0.059
34	0.019	5.5	0.081	0.076
35	0.028	4.1	0.065	0.060
36	0.044	3.9	0.068	0.051
37	0.030	4.5	0.078	0.072
38	0.052	4.4	0.077	0.077
39	0.046	3.9	0.077	0.072
40	0.032	4.0	0.067	0.062
41	0.022	3.5	0.062	0.065
42	0.018	5.0	0.060	0.060
43	0.008	4.3	0.059	0.069
44	0.042	2.8	0.057	0.070
45	0.017	1.6	0.042	0.058
46	0.019	0.1	0.052	0.040
47	0.010	4.3	0.079	0.062
48	0.030	4.4	0.090	0.058

Table B-23: Factors for calculating washing machine demand on Sundays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.8 Washing machines - Economy 7 tariff – Other weekdays

Half Hour No.	Sine amplitude values $S_{wet\ HH}$	Sine phase Values $\Phi_{wet\ HH}$	Sine constant values $K_{wet\ HH}$	Standard deviation values σ_{wet}
1	0.018	5.0	0.059	0.043
2	0.024	4.4	0.039	0.046
3	0.035	4.1	0.036	0.046
4	0.070	4.3	0.054	0.070
5	0.031	4.0	0.048	0.051
6	0.011	6.1	0.111	0.079
7	0.057	6.1	0.097	0.077
8	0.111	6.1	0.136	0.088
9	0.058	6.1	0.098	0.084
10	0.025	6.1	0.071	0.062
11	0.011	5.5	0.131	0.079
12	0.053	5.6	0.120	0.079
13	0.034	0	0.112	0.085
14	0.072	0.1	0.163	0.094
15	0.010	4.7	0.134	0.085
16	0.025	0.4	0.172	0.104
17	0.024	6.2	0.169	0.093
18	0.021	5.4	0.183	0.110
19	0.024	5.9	0.176	0.102
20	0.033	5.1	0.200	0.113
21	0.044	4.5	0.189	0.114
22	0.024	4.7	0.162	0.103
23	0.026	4.0	0.142	0.093
24	0.035	4.6	0.132	0.094
25	0.029	5.0	0.116	0.097
26	0.039	4.9	0.107	0.078
27	0.024	4.3	0.094	0.085
28	0.027	4.6	0.089	0.082
29	0.007	4.8	0.074	0.068
30	0.015	4.0	0.071	0.066
31	0.027	4.3	0.066	0.064
32	0.009	4.0	0.062	0.066
33	0.012	4.7	0.056	0.062
34	0.018	4.8	0.053	0.058
35	0.011	4.4	0.051	0.060
36	0.012	4.7	0.064	0.062
37	0.023	5.0	0.068	0.075
38	0.023	4.8	0.062	0.065
39	0.010	4.7	0.068	0.071
40	0.001	3.5	0.064	0.061
41	0.007	5.4	0.042	0.048
42	0.010	4.8	0.042	0.048
43	0.008	4.5	0.036	0.046
44	0.012	4.9	0.028	0.045
45	0.010	4.8	0.024	0.040
46	0.003	5.2	0.031	0.039
47	0.005	5.8	0.061	0.056
48	0.004	4.7	0.082	0.048

Table B-24: Factors for calculating washing machine demand on other weekdays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.9 Tumble-dryers - Unrestricted tariff – Mondays

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.017	3.7	0.028	0.028
2	0.014	3.5	0.012	0.038
3	0.008	3.8	0.006	0.023
4	0	-	0.001	0.004
5	0	-	0.001	0.002
6	0	-	0.001	0.002
7	0	-	0.001	0.002
8	0.004	4.0	0.003	0.014
9	0	-	0.005	0.024
10	0	-	0.005	0.019
11	0.010	4.8	0.015	0.043
12	0.022	5.6	0.031	0.060
13	0.035	6.2	0.046	0.066
14	0.026	5.9	0.043	0.063
15	0.034	5.4	0.050	0.061
16	0.019	5.5	0.073	0.075
17	0.005	3.5	0.092	0.100
18	0.027	3.9	0.115	0.113
19	0.040	5.3	0.114	0.120
20	0.032	5.3	0.108	0.104
21	0.051	4.3	0.119	0.123
22	0.048	4.6	0.170	0.109
23	0.107	5.4	0.205	0.137
24	0.116	5.5	0.220	0.119
25	0.058	4.9	0.208	0.133
26	0.124	5.2	0.215	0.128
27	0.125	5.2	0.229	0.130
28	0.058	5.2	0.202	0.146
29	0.117	4.9	0.181	0.131
30	0.103	4.6	0.163	0.123
31	0.086	4.5	0.162	0.148
32	0.088	4.9	0.172	0.147
33	0.110	5.2	0.174	0.141
34	0.124	5.2	0.204	0.177
35	0.118	4.8	0.232	0.172
36	0.156	4.7	0.225	0.144
37	0.162	4.8	0.206	0.150
38	0.100	4.8	0.184	0.143
39	0.024	4.8	0.168	0.140
40	0.034	4.2	0.131	0.107
41	0.042	4.7	0.094	0.101
42	0.024	4.7	0.090	0.091
43	0.045	5.5	0.095	0.108
44	0.009	5.3	0.100	0.114
45	0.011	0.2	0.084	0.108
46	0.036	0.2	0.072	0.096
47	0.009	3.4	0.072	0.098
48	0.023	3.1	0.062	0.078

Table B-25: Factors for calculating tumble-dryer demand on Mondays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.10 Tumble-dryers - Unrestricted tariff – Saturdays

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.018	3.9	0.018	0.044
2	0.005	4.5	0.009	0.029
3	0.003	4.4	0.015	0.045
4	0.009	4.7	0.011	0.040
5	0.014	5.4	0.009	0.035
6	0.011	5.4	0.007	0.032
7	0.005	5.4	0.004	0.019
8	0	-	0.001	0.002
9	0	-	0.003	0.019
10	0	-	0.002	0.009
11	0.009	5.3	0.007	0.032
12	0.005	4.7	0.010	0.032
13	0.023	5.5	0.024	0.065
14	0.016	5.9	0.024	0.051
15	0.016	0.0	0.023	0.048
16	0.021	0.5	0.037	0.061
17	0.017	4.4	0.075	0.085
18	0.023	5.9	0.081	0.084
19	0.040	5.6	0.102	0.120
20	0.029	4.6	0.132	0.114
21	0.043	5.6	0.159	0.129
22	0.037	5.2	0.171	0.128
23	0.116	5.2	0.212	0.156
24	0.148	5.3	0.206	0.163
25	0.078	4.8	0.185	0.145
26	0.078	4.8	0.194	0.160
27	0.103	4.4	0.198	0.159
28	0.094	4.9	0.219	0.166
29	0.112	5.0	0.175	0.144
30	0.101	4.7	0.197	0.154
31	0.101	4.9	0.208	0.165
32	0.106	4.9	0.197	0.154
33	0.074	4.7	0.163	0.126
34	0.087	4.7	0.174	0.119
35	0.065	5.2	0.185	0.142
36	0.108	5.1	0.205	0.152
37	0.087	4.9	0.178	0.129
38	0.107	4.9	0.168	0.162
39	0.084	5.2	0.167	0.165
40	0.052	5.2	0.119	0.140
41	0.028	6.2	0.093	0.107
42	0.067	6.2	0.103	0.105
43	0.032	5.9	0.096	0.114
44	0.029	3.9	0.080	0.104
45	0.020	4.5	0.058	0.097
46	0.004	3.5	0.039	0.064
47	0.012	3.2	0.043	0.072
48	0.005	4.0	0.038	0.068

Table B-26: Factors for calculating tumble-dryer demand on Saturdays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.11 Tumble-dryers - Unrestricted tariff – Sundays

Half Hour No.	Sine amplitude values $s_{wet\ HH}$	Sine phase Values $\Phi_{wet\ HH}$	Sine constant values $K_{wet\ HH}$	Standard deviation values σ_{wet}
1	0.013	5.8	0.021	0.045
2	0.006	4.7	0.018	0.047
3	0.003	5.3	0.012	0.031
4	0.006	6.1	0.011	0.036
5	0.005	5.5	0.009	0.038
6	0.003	5.4	0.004	0.014
7	0	-	0.001	0.002
8	0	-	0.003	0.013
9	0	-	0.003	0.015
10	0	-	0.002	0.013
11	0	-	0.006	0.025
12	0.017	3.3	0.012	0.034
13	0.005	4.0	0.019	0.046
14	0.007	2.4	0.022	0.048
15	0.032	4.9	0.046	0.077
16	0.057	5.1	0.068	0.083
17	0.043	5.2	0.069	0.080
18	0.045	5.5	0.075	0.086
19	0.057	5.3	0.083	0.093
20	0.064	5.2	0.121	0.105
21	0.034	5.2	0.160	0.121
22	0.090	5.1	0.204	0.129
23	0.072	5.1	0.208	0.131
24	0.115	4.8	0.232	0.131
25	0.170	4.7	0.253	0.136
26	0.134	4.7	0.214	0.152
27	0.08	5.0	0.226	0.153
28	0.099	4.6	0.219	0.145
29	0.092	4.9	0.195	0.147
30	0.100	4.8	0.173	0.130
31	0.091	4.4	0.169	0.149
32	0.155	4.7	0.195	0.155
33	0.161	4.6	0.207	0.178
34	0.158	4.8	0.261	0.185
35	0.199	5.0	0.257	0.185
36	0.202	4.8	0.250	0.156
37	0.168	4.7	0.223	0.146
38	0.121	4.7	0.184	0.127
39	0.154	4.7	0.194	0.132
40	0.098	4.5	0.196	0.128
41	0.118	4.7	0.164	0.125
42	0.129	4.8	0.140	0.111
43	0.063	4.3	0.137	0.116
44	0.084	4.1	0.149	0.109
45	0.044	3.6	0.131	0.102
46	0.014	3.0	0.088	0.090
47	0.024	3.3	0.090	0.108
48	0.017	3.8	0.046	0.067

Table B-27: Factors for calculating tumble-dryer demand on Sundays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.12 Tumble-dryers - Unrestricted tariff – Other weekdays

Half Hour No.	Sine amplitude values S_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.010	2.8	0.028	0.062
2	0.005	3.5	0.017	0.049
3	0.005	3.4	0.010	0.033
4	0.004	4.3	0.006	0.028
5	0	-	0.007	0.043
6	0.001	3.7	0.002	0.012
7	0.001	3.7	0.002	0.016
8	0	-	0.003	0.018
9	0	-	0.002	0.013
10	0	-	0.004	0.019
11	0	3.7	0.015	0.050
12	0.033	5.6	0.029	0.065
13	0.035	5.6	0.042	0.076
14	0.027	5.5	0.052	0.081
15	0.025	5.7	0.060	0.080
16	0.028	6.1	0.073	0.085
17	0.030	5.9	0.087	0.102
18	0.033	4.7	0.085	0.096
19	0.050	5.1	0.082	0.101
20	0.060	4.9	0.092	0.117
21	0.075	5.0	0.121	0.118
22	0.077	5.0	0.137	0.121
23	0.069	5.0	0.143	0.125
24	0.080	5.2	0.133	0.118
25	0.088	5.2	0.145	0.138
26	0.104	5.3	0.154	0.131
27	0.095	5.1	0.139	0.134
28	0.080	5.1	0.126	0.129
29	0.090	5.0	0.129	0.141
30	0.082	4.8	0.126	0.139
31	0.068	5.1	0.116	0.121
32	0.099	5.2	0.120	0.117
33	0.094	4.9	0.136	0.124
34	0.109	5.2	0.158	0.128
35	0.093	5.3	0.163	0.131
36	0.086	5.4	0.156	0.121
37	0.081	5.1	0.135	0.119
38	0.046	5.3	0.129	0.127
39	0.019	5.3	0.107	0.117
40	0.024	0.1	0.103	0.111
41	0.038	0.1	0.092	0.101
42	0.027	0.1	0.085	0.094
43	0.010	0.6	0.079	0.096
44	0.004	5.2	0.082	0.096
45	0.010	3.1	0.079	0.090
46	0.013	2.2	0.061	0.080
47	0.020	2.5	0.055	0.078
48	0.018	2.6	0.038	0.065

Table B-28: Factors for calculating tumble-dryer demand on other weekdays for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.13 Tumble-dryers - Economy 7 tariff – Mondays

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.005	2.3	0.014	0.045
2	0.003	5.7	0.009	0.027
3	0.015	5.2	0.008	0.034
4	0.011	5.0	0.007	0.033
5	0.010	4.7	0.029	0.058
6	0.058	4.0	0.061	0.075
7	0.033	3.7	0.051	0.062
8	0.055	3.1	0.080	0.100
9	0.023	4.2	0.034	0.072
10	0.010	4.7	0.014	0.038
11	0.006	5.6	0.012	0.035
12	0.008	5.8	0.008	0.028
13	0.006	3.3	0.021	0.048
14	0.019	3.2	0.027	0.055
15	0.036	4.0	0.064	0.066
16	0.089	3.9	0.098	0.101
17	0.097	4.0	0.094	0.091
18	0.110	4.1	0.095	0.095
19	0.075	4.2	0.099	0.102
20	0.046	4.3	0.120	0.100
21	0.064	4.2	0.124	0.117
22	0.056	4.5	0.139	0.119
23	0.048	4.7	0.137	0.102
24	0.095	4.8	0.149	0.091
25	0.108	4.6	0.179	0.132
26	0.108	4.6	0.172	0.115
27	0.093	4.8	0.147	0.124
28	0.098	4.6	0.135	0.125
29	0.114	4.5	0.132	0.114
30	0.138	4.8	0.132	0.105
31	0.087	4.8	0.095	0.087
32	0.086	4.9	0.111	0.097
33	0.136	4.8	0.153	0.135
34	0.147	4.9	0.176	0.146
35	0.095	5.0	0.114	0.101
36	0.082	4.8	0.100	0.112
37	0.080	4.8	0.110	0.099
38	0.059	5.0	0.104	0.100
39	0.057	4.6	0.109	0.099
40	0.018	4.6	0.076	0.082
41	0.027	6.0	0.040	0.051
42	0.029	5.6	0.045	0.073
43	0.009	3.3	0.041	0.059
44	0.004	5.2	0.016	0.045
45	0.011	5.8	0.019	0.048
46	0.010	5.9	0.012	0.037
47	0.005	3.8	0.003	0.015
48	0.007	3.0	0.006	0.030

Table B-29: Factors for calculating tumble-dryer demand on Mondays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.14 Tumble-dryers - Economy 7 tariff – Saturdays

Half Hour No.	Sine amplitude values $s_{wet\ HH}$	Sine phase Values $\Phi_{wet\ HH}$	Sine constant values $K_{wet\ HH}$	Standard deviation values σ_{wet}
1	0.013	4.8	0.009	0.030
2	0.007	6.0	0.011	0.039
3	0.013	5.8	0.009	0.030
4	0.07	4.4	0.014	0.033
5	0.012	3.1	0.023	0.042
6	0.054	4.3	0.057	0.066
7	0.03	5.1	0.069	0.099
8	0.057	3.4	0.075	0.083
9	0.029	3.8	0.029	0.046
10	0.007	3.6	0.008	0.017
11	0.013	3.0	0.010	0.032
12	0.013	2.7	0.012	0.042
13	0.013	4.7	0.010	0.028
14	0.016	4.8	0.011	0.029
15	0.005	5.2	0.015	0.036
16	0.042	4.1	0.051	0.084
17	0.058	4.2	0.092	0.122
18	0.064	3.8	0.103	0.128
19	0.062	3.8	0.116	0.113
20	0.05	3.9	0.131	0.124
21	0.08	3.9	0.164	0.125
22	0.082	4.1	0.165	0.135
23	0.049	3.6	0.192	0.144
24	0.059	3.9	0.209	0.157
25	0.07	4.5	0.184	0.133
26	0.122	4.8	0.203	0.135
27	0.133	4.8	0.223	0.172
28	0.09	4.8	0.194	0.140
29	0.154	4.7	0.190	0.137
30	0.127	4.7	0.178	0.137
31	0.125	5.1	0.193	0.118
32	0.158	4.9	0.200	0.137
33	0.128	4.8	0.190	0.161
34	0.075	4.8	0.145	0.134
35	0.077	4.8	0.130	0.157
36	0.071	4.8	0.112	0.129
37	0.038	4.7	0.111	0.113
38	0.06	4.7	0.122	0.110
39	0.057	4.3	0.092	0.097
40	0.055	3.9	0.079	0.089
41	0.048	4.2	0.070	0.089
42	0.008	3.8	0.050	0.077
43	0.009	5.3	0.049	0.067
44	0.022	5.0	0.035	0.074
45	0.011	5.0	0.011	0.026
46	0.005	5.4	0.005	0.022
47	0.008	5.8	0.006	0.031
48	0	0	0.004	0.014

Table B-30: Factors for calculating tumble-dryer demand on Saturdays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.15 Tumble-dryers - Economy 7 tariff – Sundays

Half Hour No.	Sine amplitude values S_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.17	4.3	0.013	0.048
2	0.02	3.9	0.018	0.057
3	0.014	4.1	0.015	0.043
4	0.007	4.8	0.020	0.047
5	0.024	2.2	0.032	0.049
6	0.048	3.9	0.060	0.057
7	0.042	4.8	0.072	0.073
8	0.039	4.0	0.099	0.083
9	0.018	4.0	0.037	0.052
10	0.016	4.5	0.021	0.045
11	0.007	3.8	0.014	0.040
12	0.027	1.6	0.018	0.048
13	0.012	0.7	0.015	0.039
14	0.010	6.0	0.023	0.062
15	0.040	4.2	0.040	0.070
16	0.047	4.3	0.060	0.066
17	0.052	4.2	0.071	0.072
18	0.060	3.8	0.079	0.072
19	0.057	3.7	0.090	0.101
20	0.050	4.6	0.127	0.109
21	0.135	4.5	0.164	0.144
22	0.124	4.4	0.170	0.132
23	0.109	4.7	0.180	0.143
24	0.066	4.0	0.199	0.126
25	0.078	4.3	0.207	0.136
26	0.104	4.7	0.208	0.145
27	0.096	4.8	0.213	0.150
28	0.134	4.9	0.182	0.148
29	0.092	4.7	0.147	0.127
30	0.080	4.8	0.146	0.129
31	0.085	4.3	0.157	0.127
32	0.080	4.0	0.150	0.126
33	0.065	4.2	0.115	0.113
34	0.042	4.2	0.093	0.105
35	0.028	3.4	0.077	0.099
36	0.035	3.5	0.075	0.109
37	0.049	4.3	0.096	0.111
38	0.031	4.5	0.090	0.088
39	0.018	4.7	0.078	0.088
40	0.030	4.8	0.056	0.077
41	0.055	4.9	0.056	0.068
42	0.026	4.4	0.031	0.055
43	0.020	4.5	0.031	0.060
44	0.008	5.3	0.027	0.051
45	0.010	3.7	0.028	0.055
46	0.007	4.0	0.013	0.036
47	0.021	4.4	0.015	0.046
48	0.019	4.6	0.018	0.045

Table B-31: Factors for calculating tumble-dryer demand on Sundays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.16 Tumble-dryers - Economy 7 tariff – Other weekdays

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.004	4.8	0.004	0.021
2	0.005	0.2	0.006	0.029
3	0.008	5.5	0.008	0.031
4	0.006	0.1	0.014	0.035
5	0.008	1.9	0.027	0.052
6	0.041	4.3	0.055	0.069
7	0.034	4.7	0.052	0.061
8	0.016	3.6	0.074	0.084
9	0.013	5.2	0.044	0.068
10	0.004	3.8	0.020	0.042
11	0.002	3.4	0.008	0.029
12	0.004	4.8	0.008	0.029
13	0.014	4.8	0.016	0.043
14	0.014	4.7	0.032	0.056
15	0.036	4.6	0.058	0.085
16	0.050	3.9	0.082	0.092
17	0.057	3.9	0.086	0.100
18	0.038	3.7	0.063	0.080
19	0.048	4.0	0.083	0.103
20	0.046	4.3	0.093	0.100
21	0.055	4.7	0.105	0.099
22	0.052	4.5	0.109	0.109
23	0.060	4.2	0.109	0.102
24	0.064	4.3	0.109	0.108
25	0.056	4.5	0.103	0.103
26	0.059	4.4	0.101	0.101
27	0.044	4.5	0.093	0.101
28	0.047	4.2	0.094	0.105
29	0.042	4.4	0.086	0.103
30	0.059	4.5	0.082	0.100
31	0.060	4.4	0.084	0.108
32	0.057	4.5	0.097	0.102
33	0.071	4.7	0.114	0.118
34	0.063	4.7	0.110	0.123
35	0.048	4.8	0.106	0.113
36	0.045	4.9	0.094	0.101
37	0.038	4.7	0.082	0.103
38	0.030	4.8	0.086	0.106
39	0.022	4.9	0.084	0.104
40	0.022	4.8	0.077	0.093
41	0.010	4.4	0.065	0.083
42	0.003	3.7	0.047	0.070
43	0.005	3.8	0.037	0.069
44	0.004	1.5	0.030	0.058
45	0.010	1.7	0.021	0.046
46	0.007	2	0.014	0.037
47	0	-	0.011	0.036
48	0.004	4.9	0.008	0.031

Table B-32: Factors for calculating tumble-dryer demand on other weekdays for Economy-7 tariff consumers (half-hourly, group average – based on LRG data)

B5.17 Dishwashers - Unrestricted tariff

Half Hour No.	Sine amplitude values s_{wet_HH}	Sine phase Values Φ_{wet_HH}	Sine constant values K_{wet_HH}	Standard deviation values σ_{wet}
1	0.004	2.6	0.058	0.071
2	0.015	2.4	0.053	0.053
3	0	-	0.017	0.036
4	0	-	0.009	0.032
5	0	-	0.008	0.030
6	0	-	0.006	0.023
7	0	-	0.006	0.025
8	0	-	0.003	0.016
9	0	-	0.001	0.007
10	0	-	0.001	0.006
11	0	-	0.001	0.011
12	0	-	0.001	0.013
13	0	-	0.001	0.007
14	0	-	0.002	0.015
15	0.001	2.0	0.009	0.034
16	0.012	1.0	0.025	0.053
17	0.016	0.5	0.072	0.094
18	0	-	0.104	0.114
19	0	-	0.114	0.112
20	0.005	3.4	0.117	0.106
21	0	-	0.137	0.113
22	0	-	0.128	0.110
23	0	-	0.094	0.102
24	0	-	0.068	0.088
25	0	-	0.060	0.087
26	0	-	0.051	0.073
27	0	-	0.061	0.082
28	0	-	0.079	0.098
29	0	-	0.083	0.102
30	0	-	0.085	0.112
31	0.022	5.2	0.078	0.101
32	0.022	5.1	0.068	0.094
33	0.017	5.3	0.060	0.088
34	0.014	4.7	0.056	0.081
35	0.006	5.2	0.053	0.086
36	0.016	5.0	0.061	0.095
37	0.015	5.0	0.067	0.091
38	0.017	5.5	0.094	0.095
39	0.025	5.0	0.143	0.133
40	0.009	5.8	0.196	0.146
41	0.037	5.7	0.212	0.140
42	0.024	0	0.195	0.134
43	0.024	0.1	0.182	0.141
44	0.001	0	0.187	0.132
45	0.015	0	0.172	0.125
46	0.012	5.7	0.130	0.111
47	0.004	4.4	0.093	0.091
48	0.005	5.5	0.068	0.080

Table B-33: Factors for calculating dishwasher demand for unrestricted tariff consumers (half-hourly, group average – based on LRG data)

B5.18 Dishwashers - Economy 7 tariff

Half Hour No.	Sine amplitude values swet_HH	Sine phase Values Φwet_HH	Sine constant values Kwet_HH	Standard deviation values σwet
1	0.063	3.8	0.085	0.128
2	0.062	4.2	0.092	0.125
3	0.062	3.8	0.120	0.119
4	0.073	4.4	0.157	0.150
5	0.084	6.1	0.166	0.146
6	0.072	0.3	0.095	0.108
7	0.080	0.9	0.081	0.118
8	0.057	1.4	0.061	0.094
9	0.007	0.2	0.073	0.097
10	0.042	6.1	0.097	0.109
11	0.083	6.0	0.102	0.110
12	0.006	6.0	0.015	0.050
13	0	-	0.012	0.051
14	0.002	6.0	0.018	0.061
15	0.005	0.9	0.048	0.109
16	0.002	0	0.067	0.123
17	0.007	5.2	0.087	0.134
18	0.022	4.9	0.075	. 0.121
19	0.008	4.4	0.087	0.141
20	0.019	4.9	0.106	0.151
21	0.026	4.4	0.112	0.151
22	0.037	4.7	0.110	0.145
23	0.034	4.5	0.091	0.141
24	0.011	4.8	0.062	0.107
25	0.068	4.7	0.068	0.125
26	0.021	5.0	0.064	0.124
27	0.015	4.8	0.061	0.112
28	0.008	5.0	0.076	0.126
29	0.015	4.7	0.100	0.150
30	0.022	4.3	0.115	0.170
31	0.024	4.4	0.087	0.144
32	0.018	4.7	0.062	0.127
33	0.018	4.8	0.048	0.114
34	0.011	4.7	0.043	0.097
35	0.012	4.6	0.040	0.094
36	0.010	4.8	0.037	0.089
37	0.005	4.7	0.046	0.100
38	0.017	4.7	0.058	0.112
39	0.043	4.6	0.100	0.149
40	0.026	4.5	0.117	0.155
41	0.026	4.3	0.125	0.152
42	0.009	3.6	0.098	0.138
43	0.007	3.8	0.070	0.124
44	0.006	3.4	0.048	0.106
45	0.004	4.1	0.047	0102
46	0.010	3.9	0.065	0.120
47	0.015	3.2	0.120	0.146
48	0.029	3.7	0.120	0.151

Table B-34: Factors for calculating dishwasher demand for Economy-7 tariff consumers (half-hourly, group average – based on LRG data

B5.19 Estimated peak annual diversified demand (kW) values, p_{wet}

Year	Washing Machine	Tumble-Dryer	Dishwasher
1970	0.307	0.241	0.884
1975	0.287	0.237	0.872
1980	0.272	0.239	0.854
1985	0.269	0.300	0.790
1990	0.258	0.349	0.657
1995	0.239	0.349	0.573
1996	0.235	0.347	0.560
1998	0.227	0.344	0.535
2000	0.220	0.342	0.514
2005	0.207	0.332	0.460
2010	0.197	0.321	0.413
2015	0.189	0.307	0.385
2020	0.183	0.294	0.374

Table B-35: Estimated annual peak diversified demands for wet appliances (annual, half-hourly, group average – based on trends in the total annual demand of an average appliance [DEFRA, 2001])

B.6 Lighting appliances

B6.1 Lighting – Weekdays

Half Hour Ref.	Min. level		Max. level		Sine 1		Sine 2		Constant	Sine std dev
	Value d_{lights_min}	Std dev σ_{lights_min}	Value d_{lights_max}	Std dev σ_{lights_max}	Scale $s_{1\_lights\_HH}$	Phase $\varphi_{1\_lights\_HH}$	Scale $s_{2\_lights\_HH}$	Phase $\varphi_{2\_lights\_HH}$	k_{lights_HH}	σ_{lights_sine}
1	0	0	1	0	0	0	0.011	5.8	0.263	0.049
2	0	0	1	0	0	0	0.004	5.9	0.186	0.040
3	0	0	1	0	0	0	0.003	4.3	0.140	0.035
4	0	0	1	0	0	0	0.006	3.7	0.110	0.026
5	0	0	1	0	0	0	0.008	3.9	0.092	0.022
6	0	0	1	0	0	0	0.009	4.0	0.079	0.018
7	0	0	1	0	0	0	0.006	3.8	0.069	0.016
8	0	0	1	0	0	0	0.005	3.9	0.065	0.014
9	0	0	1	0	0	0	0.005	3.9	0.062	0.014
10	0	0	1	0	0.006	0.9	0.010	3.6	0.057	0.013
11	0	0	1	0	0.005	0.5	0.013	3.5	0.058	0.014
12	0	0	1	0	0.009	4.0	0.007	4.1	0.069	0.014
13	0	0	0.091	0.017	0.015	4.2	0.045	4.7	0.111	0.013
14	0.051	0.013	0.169	0.035	0.114	4.7	0.030	4.3	0.149	0.026
15	0.080	0.025	0.318	0.063	0.035	4.4	0.295	4.2	0.092	0.058
16	0.095	0.045	0.452	0.133	0.026	5.8	0.498	4.1	0.008	0.072
17	0.098	0.139	1	0	0.063	4.9	0.453	4.2	-0.028	0.065
18	0.077	0.024	1	0	0.048	4.6	0.352	4.2	-0.086	0.061
19	0.064	0.024	1	0	0.021	5.6	0.255	4.1	-0.039	0.062
20	0.060	0.027	1	0	0.022	5.5	0.206	4.1	-0.027	0.056
21	0.057	0.026	1	0	0.031	4.6	0.182	4.2	-0.028	0.053
22	0.057	0.027	1	0	0.018	5.0	0.164	4.1	-0.022	0.049
23	0.060	0.029	1	0	0.027	4.7	0.153	4.2	-0.025	0.041
24	0.057	0.029	1	0	0.017	4.7	0.159	4.2	-0.030	0.040
25	0.054	0.024	1	0	0.009	4.7	0.139	4.2	-0.009	0.042
26	0.056	0.030	1	0	0.019	5.6	0.145	4.2	-0.023	0.042
27	0.059	0.032	1	0	0.010	6.1	0.146	4.2	-0.013	0.041
28	0.055	0.024	1	0	0.013	0.0	0.145	4.1	-0.007	0.047
29	0.054	0.031	1	0	0.018	5.1	0.147	4.2	-0.016	0.047
30	0.054	0.025	1	0	0.029	5.8	0.153	4.0	-0.018	0.053
31	0.058	0.026	1	0	0.054	5.1	0.184	4.1	-0.042	0.064
32	0.064	0.031	1	0	0.188	4.9	0.269	4.1	-0.141	0.078
33	0.073	0.040	1	0	0.351	4.9	0.347	4.0	-0.224	0.082
34	0.083	0.046	1	0	0.607	4.9	0.107	4.4	-0.016	0.069
35	0.087	0.040	0.805	0.060	0.564	4.9	0.157	4.3	0.129	0.085
36	0.087	0.038	0.826	0.064	0.560	4.8	0.333	4.5	0.192	0.103
37	0.094	0.042	0.847	0.063	0.476	4.7	0.554	4.5	0.247	0.092
38	0.115	0.054	0.848	0.060	0.439	4.7	0.728	4.5	0.326	0.079
39	0.127	0.069	0.839	0.058	0.370	4.7	0.705	4.5	0.459	0.086
40	0.125	0.054	0.813	0.050	0.256	4.7	0.460	4.5	0.581	0.079
41	0.149	0.089	0.789	0.053	0.370	4.7	0.322	4.5	0.712	0.055
42	0	0	0.782	0.056	0.473	4.7	0.188	4.5	0.823	0.068
43	0	0	0.759	0.063	0.390	4.7	0.322	4.7	0.980	0.055
44	0	0	0.743	0.044	0.375	4.8	0.012	3.5	0.801	0.057
45	0	0	0.706	0.043	0.172	4.8	0	0	0.697	0.042
46	0	0	0.623	0.045	0.083	5.2	0	0	0.590	0.042
47	0	0	1	0	0.049	5.3	0	0	0.472	0.047
48	0	0	1	0	0.035	5.3	0	0	0.366	0.048

Table B-36: Factors for calculating lighting demand on weekdays (half-hourly, group average – based on LRG data

B6.2 Lighting – Saturdays

Half Hour Ref.	Min. level		Max. level		Sine 1		Sine 2		Con-stant	Sine std dev
	Value d_{lights_min}	Std dev σ_{lights_min}	Value d_{lights_max}	Std dev σ_{lights_max}	Scale $s_{1\_lights\_HH}$	Phase $\varphi_{1\_lights\_HH}$	Scale $s_{2\_lights\_HH}$	Phase $\varphi_{2\_lights\_HH}$	k_{lights_HH}	σ_{lights_sine}
1	0	0	1	0	0.042	5.7	0.013	3.9	0.312	0.032
2	0	0	1	0	0.034	5.8	0.011	3.4	0.224	0.030
3	0	0	1	0	0.026	5.6	0.007	3.4	0.163	0.028
4	0	0	1	0	0.021	5.4	0.006	3.4	0.128	0.026
5	0	0	1	0	0.018	5.5	0.009	3.1	0.106	0.024
6	0	0	1	0	0.014	5.5	0.006	3.2	0.092	0.020
7	0	0	1	0	0.008	5.9	0.006	3.5	0.081	0.017
8	0	0	1	0	0.006	5.7	0.003	3.2	0.072	0.016
9	0	0	1	0	0.005	5.6	0.004	3.2	0.066	0.015
10	0	0	1	0	0.004	5.5	0.004	3.4	0.063	0.015
11	0	0	1	0	0.006	5.6	0.009	3.4	0.061	0.014
12	0	0	1	0	0.007	5.6	0.008	3.6	0.063	0.014
13	0	0	0.081	0.019	0.014	4.0	0.045	4.7	0.097	0.015
14	0.049	0.014	0.102	0.025	0.039	4.3	0.078	4.8	0.111	0.012
15	0.054	0.016	0.153	0.025	0.097	4.5	0287	4.2	0.031	0.006
16	0.065	0.020	0.211	0.037	0.066	5.3	0.290	4.1	0.004	0.032
17	0.075	0.021	0.275	0.032	0.019	5.6	0.299	4.1	-0.019	0.044
18	0.077	0.024	1	0	0.041	4.6	0.254	4.3	0.003	0.039
19	0.087	0.025	1	0	0.037	5.7	0.206	4.1	0.020	0.045
20	0.075	0.022	1	0	0.038	5.0	0.203	4.2	0.010	0.059
21	0.069	0.023	1	0	0.045	4.6	0.212	4.3	-0.002	0.049
22	0.065	0.022	1	0	0.057	4.9	0.090	4.2	0.054	0.048
23	0.069	0.027	1	0	0.058	4.9	0.087	4.2	0.053	0.049
24	0.062	0.028	1	0	0.060	5.2	0.084	4.2	0.049	0.039
25	0.059	0.023	1	0	0.056	5.3	0.087	4.2	0.044	0.038
26	0.064	0.026	1	0	0.054	5.3	0.090	4.1	0.044	0.043
27	0.063	0.028	1	0	0.045	5.1	0.093	4.2	0.049	0.056
28	0.052	0.019	1	0	0.044	5.1	0.093	4.2	0.058	0.048
29	0.050	0.019	1	0	0.054	5.5	0.099	4.2	0.051	0.051
30	0.049	0.021	1	0	0.051	5.5	0.122	4.0	0.045	0.052
31	0.045	0.019	1	0	0.092	5.4	0.126	4.0	0.042	0.055
32	0.049	0.027	1	0	0.165	5.1	0.132	4.2	0.032	0.071
33	0.061	0.043	1	0	0.308	5.0	0.317	4.1	-0.115	0.072
34	0.069	0.036	1	0	0.605	4.9	0.107	4.4	-0.015	0.064
35	0.072	0.037	0.760	0.036	0.609	5.0	0.209	4.1	0.104	0.036
36	0.072	0.051	0.789	0.042	0.480	5.1	0.439	4.1	0.156	0.042
37	0.086	0.044	0.819	0.050	0.470	5.3	0.660	4.1	0.204	0.043
38	0.097	0.060	0.816	0.055	0.630	5.3	0.890	4.1	0.340	0.055
39	0.126	0.054	0.797	0.054	0.590	5.6	1.310	4.1	0.348	0.023
40	0.141	0.065	0.769	0.050	0.540	5.6	0.910	4.1	0.640	0.042
41	0.174	0.094	0.741	0.054	0.550	5.6	0.760	4.0	0.750	0.071
42	0	0	0.719	0.047	0.353	5.6	0.440	4.0	0.701	0.070
43	0	0	0.703	0.049	0.308	5.6	0.350	4.0	0.703	0.068
44	0	0	0.681	0.049	0.261	5.6	0.247	4.0	0.686	0.059
45	0	0	0.642	0.051	0.206	5.6	0.142	4.0	0.669	0.051
46	0	0	0.605	0.053	0.200	5.6	0.118	3.8	0.630	0.038
47	0	0	0.552	0.056	0.189	5.7	0.107	3.5	0.565	0.042
48	0	0	0.507	0.037	0.091	5.6	0.048	3.3	0.442	0.050

Table B-37: Factors for calculating lighting demand on Saturdays (half-hourly, group average – based on LRG data

B6.3 Lighting – Sundays

Half Hour Ref.	Min. level		Max. level		Sine 1		Sine 2		Constant	Sine std dev
	Value d_{lights_min}	Std dev σ_{lights_min}	Value d_{lights_max}	Std dev σ_{lights_max}	Scale $S_{1\_lights\_HH}$	Phase $\varphi_{1\_lights\_HH}$	Scale $S_{2\_lights\_HH}$	Phase $\varphi_{2\_lights\_HH}$	k_{lights_HH}	σ_{lights_sine}
1	0	0	1	0	0.056	5.7	0.021	3.9	0.352	0.047
2	0	0	1	0	0.046	5.7	0.008	3.9	0.267	0.039
3	0	0	1	0	0.026	5.7	0.010	3.9	0.202	0.037
4	0	0	1	0	0.012	5.7	0.010	3.8	0.152	0.027
5	0	0	1	0	0.008	5.6	0.014	3.8	0.120	0.023
6	0	0	1	0	0.004	5.8	0.015	3.9	0.097	0.022
7	0	0	1	0	0.008	6.0	0.013	3.9	0.082	0.018
8	0	0	1	0	0.004	6.0	0.010	3.9	0.075	0.017
9	0	0	1	0	0.004	6.0	0.010	3.9	0.069	0.016
10	0	0	1	0	0.003	6.0	0.010	3.9	0.064	0.015
11	0	0	1	0	0.001	6.0	0.010	3.9	0.061	0.014
12	0	0	1	0	0.001	6.0	0.010	3.9	0.059	0.015
13	0	0	1	0	0.003	5.9	0.015	4.0	0.062	0.015
14	0	0	1	0	0	0	0.028	4.3	0.071	0.018
15	0	0	1	0	0.017	5.0	0.027	4.3	0.079	0.022
16	0	0	1	0	0.022	5.2	0.046	4.2	0.089	0.023
17	0.061	0.023	1	0	0.043	4.8	0.094	4.2	0.073	0.031
18	0.066	0.023	1	0	0.056	4.9	0.096	4.0	0.082	0.035
19	0.069	0.026	1	0	0.048	4.7	0.102	4.0	0.093	0.043
20	0.072	0.024	1	0	0.051	4.6	0.107	4.0	0.085	0.049
21	0.075	0.035	1	0	0.062	4.5	0.080	4.5	0.094	0.051
22	0	0	1	0	0.083	4.8	0.004	3.3	0.131	0.039
23	0	0	1	0	0.078	4.7	0.004	3.3	0.129	0.053
24	0	0	1	0	0.080	4.8	0	0	0.126	0.041
25	0	0	1	0	0.078	4.8	0	0	0.126	0.048
26	0	0	1	0	0.075	4.7	0.003	3.2	0.121	0.046
27	0	0	1	0	0.078	4.8	0.004	3.2	0.129	0.050
28	0	0	1	0	0.074	4.8	0.016	3.7	0.126	0.046
29	0	0	1	0	0.078	4.8	0.018	3.7	0.129	0.048
30	0	0	1	0	0.082	4.9	0.031	3.6	0.131	0.045
31	0	0	1	0	0.088	4.9	0.043	3.6	0.142	0.058
32	0.060	0.023	1	0	0.160	5.0	0.072	3.6	0.138	0.079
33	0.071	0.025	1	0	0.301	5.0	0.203	3.8	0.050	0.084
34	0.078	0.041	1	0	0.477	4.8	0.120	4.4	0.133	0.075
35	0.081	0.036	1	0	0.409	5.0	0.224	3.9	0.189	0.088
36	0.085	0.039	0.799	0.043	0.509	5.0	0.438	4.1	0.148	0.088
37	0.094	0.043	0.822	0.053	0.421	5.2	0.699	4.1	0.153	0.057
38	0.109	0.055	0.819	0.049	0.657	5.2	0.927	4.1	0.248	0.050
39	0.140	0.083	0.822	0.054	0.829	5.1	0.999	4.1	0.420	0.094
40	0.181	0.115	0.798	0.061	0.831	5.1	1.001	4.1	0.588	0.072
41	0.186	0.157	0.762	0.060	0.525	5.6	0.722	4.0	0.772	0.089
42	0.195	0.076	0.747	0.072	0.525	5.7	0.740	4.1	0.969	0.068
43	0	0	0.737	0.069	0.412	5.7	0.591	4.1	0.972	0.069
44	0	0	0.708	0.061	0.060	4.9	0.300	4.8	0.774	0.053
45	0	0	0.660	0.045	0.060	4.9	0.231	4.8	0.777	0.035
46	0	0	1	0	0.025	5.1	0.020	4.8	0.545	0.043
47	0	0	1	0	0.027	5.5	0	1	0.453	0.051
48	0	0	1	0	0.028	5.5	0	1	0.351	0.044

Table B-38: Factors for calculating lighting demand on Sundays (half-hourly, group average – based on LRG data

B6.4 Estimated peak annual diversified lighting demand (kW) values

Year	Lighting peak scaling factor p_{lights}
1970	0.243
1975	0.276
1980	0.309
1985	0.335
1990	0.358
1995	0.374
1996	0.395
1998	0.424
2000	0.449
2005	0.488
2010	0.527
2015	0.243
2020	0.276

Table B-39: Estimated annual peak diversified demands for lighting appliances (annual, half-hourly, group average – based on trends in the total annual lighting demand adjusted for variations in the housing stock [DEFRA, 2001])

B.7 Miscellaneous demand

B7.1 Miscellaneous demand - Mondays

Half Hour No.	Sine amplitude values s_{misc_HH}	Sine phase Values φ_{misc_HH}	Sine constant values k_{misc_HH}	Standard deviation values σ_{misc}
1	0.046	5.2	0.154	0.038
2	0.044	5.2	0.130	0.022
3	0.040	5.3	0.114	0.020
4	0.036	5.4	0.108	0.020
5	0.045	5.6	0.095	0.018
6	0.037	5.8	0.091	0.021
7	0.038	5.3	0.102	0.018
8	0.033	5.4	0.103	0.017
9	0.033	5.3	0.102	0.018
10	0.033	5.1	0.122	0.018
11	0.044	5.3	0.118	0.023
12	0.040	5.3	0.127	0.026
13	0.050	5.1	0.172	0.030
14	0.071	5.1	0.250	0.053
15	0.067	5.0	0.324	0.059
16	0.072	5.1	0.368	0.077
17	0.077	409	0.355	0.065
18	0.077	5.2	0.324	0.076
19	0.077	5.1	0.314	0.072
20	0.085	5.0	0.333	0.062
21	0.095	4.7	0.326	0.078
22	0.099	4.9	0.320	0.070
23	0.084	4.8	0.299	0.087
24	0.099	4.9	0.273	0.089
25	0.107	5.1	0.293	0.073
26	0.088	4.9	0.258	0.064
27	0.101	4.8	0.281	0.079
28	0.106	5.1	0.289	0.073
29	0.079	5.2	0.291	0.058
30	0.078	5.2	0.288	0.072
31	0.105	5.1	0.310	0.064
32	0.123	5.2	0.325	0.074
33	0.117	5.0	0.365	0.090
34	0.121	5.1	0.437	0.098
35	0.126	4.9	0.442	0.088
36	0.127	5.1	0.466	0.090
37	0.127	5.2	0.444	0.092
38	0.131	5.1	0.427	0.095
39	0.147	5.1	0.400	0.085
40	0.134	5.1	0.403	0.064
41	0.107	5.1	0.397	0.064
42	0.104	5.2	0.391	0.075
43	0.107	4.9	0.387	0.070
44	0.117	5.0	0.356	0.060
45	0.102	5.1	0.337	0.060
46	0.091	5.3	0.282	0.052
47	0.074	5.3	0.220	0.053
48	0.068	5.1	0.172	0.036

Table B-40: Factors for calculating miscellaneous demand on Mondays (half-hourly, group average – based on LRG data)

B7.2 Miscellaneous demand – Saturdays

Half Hour No.	Sine amplitude values s_{misc_HH}	Sine phase Values φ_{misc_HH}	Sine constant values k_{misc_HH}	Standard deviation values σ_{misc}
1	0.066	5.1	0.173	0.036
2	0.056	5.2	0.148	0.032
3	0.040	5.2	0.129	0.029
4	0.040	5.1	0.120	0.022
5	0.034	5.4	0.109	0.023
6	0.040	5.3	0.107	0.023
7	0.037	5.3	0.107	0.020
8	0.040	5.3	0.107	0.018
9	0.037	5.3	0.114	0.020
10	0.033	5.1	0.126	0.022
11	0.036	5.2	0.129	0.020
12	0.039	5.2	0.124	0.020
13	0.048	5.2	0.134	0.035
14	0.049	5.4	0.193	0.029
15	0.051	5.1	0.284	0.046
16	0.056	5.5	0.320	0.051
17	0.083	5.5	0.359	0.058
18	0.068	5.2	0.400	0.062
19	0.109	5.0	0.400	0.079
20	0.110	5.2	0.395	0.065
21	0.146	4.9	0.360	0.099
22	0.158	5.1	0.326	0.096
23	0.137	5.0	0.312	0.090
24	0.108	5.1	0.269	0.083
25	0.125	4.9	0.275	0.084
26	0.131	5.0	0.259	0.094
27	0.112	5.1	0.294	0.089
28	0.107	5.1	0.295	0.077
29	0.106	5.2	0.303	0.072
30	0.100	5.4	0.304	0.077
31	0.108	5.3	0.313	0.079
32	0.102	5.1	0.316	0.077
33	0.103	5.0	0.347	0.074
34	0.155	4.9	0.387	0.089
35	0.156	4.9	0.483	0.101
36	0.153	5.0	0.458	0.106
37	0.143	4.8	0.415	0.104
38	0.149	4.8	0.409	0.090
39	0.138	5.0	0.410	0.072
40	0.137	5.1	0.408	0.059
41	0.118	5.0	0.406	0.065
42	0.108	4.9	0.375	0.067
43	0.117	4.9	0.368	0.059
44	0.103	4.9	0.342	0.055
45	0.094	4.9	0.309	0.057
46	0.093	5.1	0.282	0.050
47	0.082	5.0	0.245	0.048
48	0.065	5.2	0.195	0.050

Table B-41: Factors for calculating miscellaneous demand on Saturdays (half-hourly, group average – based on LRG data)

B7.3 Miscellaneous demand – Sundays

Half Hour No.	Sine amplitude values s_{misc_HH}	Sine phase Values φ_{misc_HH}	Sine constant values k_{misc_HH}	Standard deviation values σ_{misc}
1	0.060	5.1	0.172	0.045
2	0.045	5.0	0.144	0.039
3	0.042	5.1	0.121	0.038
4	0.046	5.2	0.110	0.032
5	0.038	5.4	0.096	0.024
6	0.044	5.5	0.098	0.026
7	0.034	5.3	0.105	0.021
8	0.032	5.2	0.105	0.018
9	0.025	5.3	0.104	0.020
10	0.036	5.3	0.120	0.019
11	0.038	5.1	0.116	0.021
12	0.039	5.1	0.116	0.023
13	0.047	5.4	0.120	0.025
14	0.040	5.2	0.158	0.027
15	0.039	5.3	0.223	0.034
16	0.054	5.3	0.279	0.037
17	0.079	5.5	0.330	0.050
18	0.100	5.3	0.376	0.053
19	0.103	5.2	0.400	0.063
20	0.102	5.3	0.429	0.064
21	0.099	5.2	0.420	0.081
22	0.121	5.2	0.423	0.094
23	0.131	5.2	0.462	0.081
24	0.134	5.3	0.458	0.092
25	0.115	5.1	0.469	0.105
26	0.118	5.0	0.459	0.101
27	0.129	5.1	0.445	0.100
28	0.120	5.1	0.436	0.084
29	0.117	5.1	0.402	0.088
30	0.109	5.3	0.399	0.066
31	0.131	5.3	0.393	0.077
32	0.118	5.2	0.377	0.062
33	0.108	5.3	0.372	0.070
34	0.115	5.2	0.393	0.088
35	0.111	4.8	0.402	0.120
36	0.112	5.1	0.427	0.097
37	0.129	5.1	0.402	0.099
38	0.157	5.0	0.410	0.078
39	0.129	5.0	0.405	0.081
40	0.120	5.2	0.384	0.083
41	0.106	5.1	0.387	0.065
42	0.098	5.1	0.374	0.068
43	0.122	5.0	0.366	0.061
44	0.096	5.0	0.335	0.062
45	0.104	5.1	0.327	0.057
46	0.091	5.2	0.290	0.046
47	0.089	5.2	0.229	0.052
48	0.058	5.2	0.181	0.045

Table B-42: Factors for calculating miscellaneous demand on Sundays (half-hourly, group average – based on LRG data)

B7.4 Miscellaneous demand – Other weekdays

Half Hour No.	Sine amplitude values $s_{misc\ HH}$	Sine phase Values $\varphi_{misc\ HH}$	Sine constant values $k_{misc\ HH}$	Standard deviation values σ_{misc}
1	0.067	5.1	0.154	0.038
2	0.056	5.1	0.128	0.032
3	0.044	5.2	0.118	0.027
4	0.044	5.3	0.110	0.022
5	0.044	5.3	0.100	0.023
6	0.041	5.3	0.103	0.020
7	0.038	5.2	0.106	0.020
8	0.035	5.2	0.107	0.019
9	0.030	5.2	0.107	0.021
10	0.039	5.2	0.125	0.020
11	0.053	5.3	0.121	0.026
12	0.046	5.1	0.128	0.025
13	0.045	5.1	0.173	0.031
14	0.062	5.3	0.257	0.038
15	0.062	5.3	0.345	0.048
16	0.083	5.3	0.400	0.059
17	0.090	5.1	0.374	0.069
18	0.084	5.3	0.356	0.064
19	0.092	5.2	0.345	0.063
20	0.092	5.1	0.332	0.073
21	0.100	5.2	0.314	0.079
22	0.099	5.3	0.295	0.084
23	0.096	5.0	0.290	0.091
24	0.103	5.1	0.274	0.096
25	0.099	5.2	0.280	0.100
26	0.092	5.1	0.251	0.099
27	0.099	5.2	0.278	0.091
28	0.097	5.3	0.287	0.094
29	0.098	5.2	0.290	0.087
30	0.108	5.3	0.296	0.077
31	0.110	5.2	0.312	0.075
32	0.123	5.2	0.330	0.079
33	0.138	5.2	0.384	0.084
34	0.149	5.2	0.438	0.094
35	0.130	4.8	0.440	0.107
36	0.148	4.8	0.476	0.106
37	0.150	4.8	0.459	0.106
38	0.151	5.0	0.444	0.089
39	0.141	5.1	0.419	0.085
40	0.142	5.0	0.398	0.078
41	0.131	4.9	0.395	0.068
42	0.140	5.0	0.393	0.068
43	0.140	4.9	0.395	0.057
44	0.110	5.0	0.359	0.056
45	0.117	5.0	0.336	0.058
46	0.101	5.0	0.288	0.055
47	0.090	4.9	0.232	0.051
48	0.071	5.0	0.191	0.041

Table B-43: Factors for calculating miscellaneous demand on other weekdays (half-hourly, group average – based on LRG data)

B7.5 Estimated peak annual diversified miscellaneous demand (kW) values

Year	Miscellaneous peak scaling factor P_{misc}
1970	0.435
1975	0.487
1980	0.539
1985	0.592
1990	0.644
1995	0.696
2000	0.748
2005	0.800
2010	0.853
2015	0.905
2020	0.957

Table B-44: Estimated annual peak diversified demands for miscellaneous appliances (annual, half-hourly, group average – based on trends in the total annual TV energy demand adjusted for variations in the housing stock [DEFRA, 2001])

Appendix C

Verification of the domestic model, layer 1
(Group, half-hourly demand)

This appendix includes verification details of the domestic model, layer 1 against the original LRG data. For further details of this part of the model, refer to Chapter 4.

The comparison between the output of the domestic model, layer 1, and the LRG data is based on a cumulative distribution function. The vertical axis shows the probability that the demand level is less than the corresponding demand value shown on the horizontal axis. Both measured and predicted values refer to the half-hourly averaged demand for a large group of domestic consumers. (Note: the modelled data includes a random element which varies slightly from one run to the next. Only a single run is included for this comparison).

Although the model is not intended to be used to provide estimates of the annual consumption, a comparison is included between the annual aggregate of the LRG measurements and the range of the annual energy demand for ten runs of the model. These are compared with estimates made for the national average household consumption or annual consumption per appliance from other research, where available.

C.1 Cooling demand

C1.1 Refrigerators

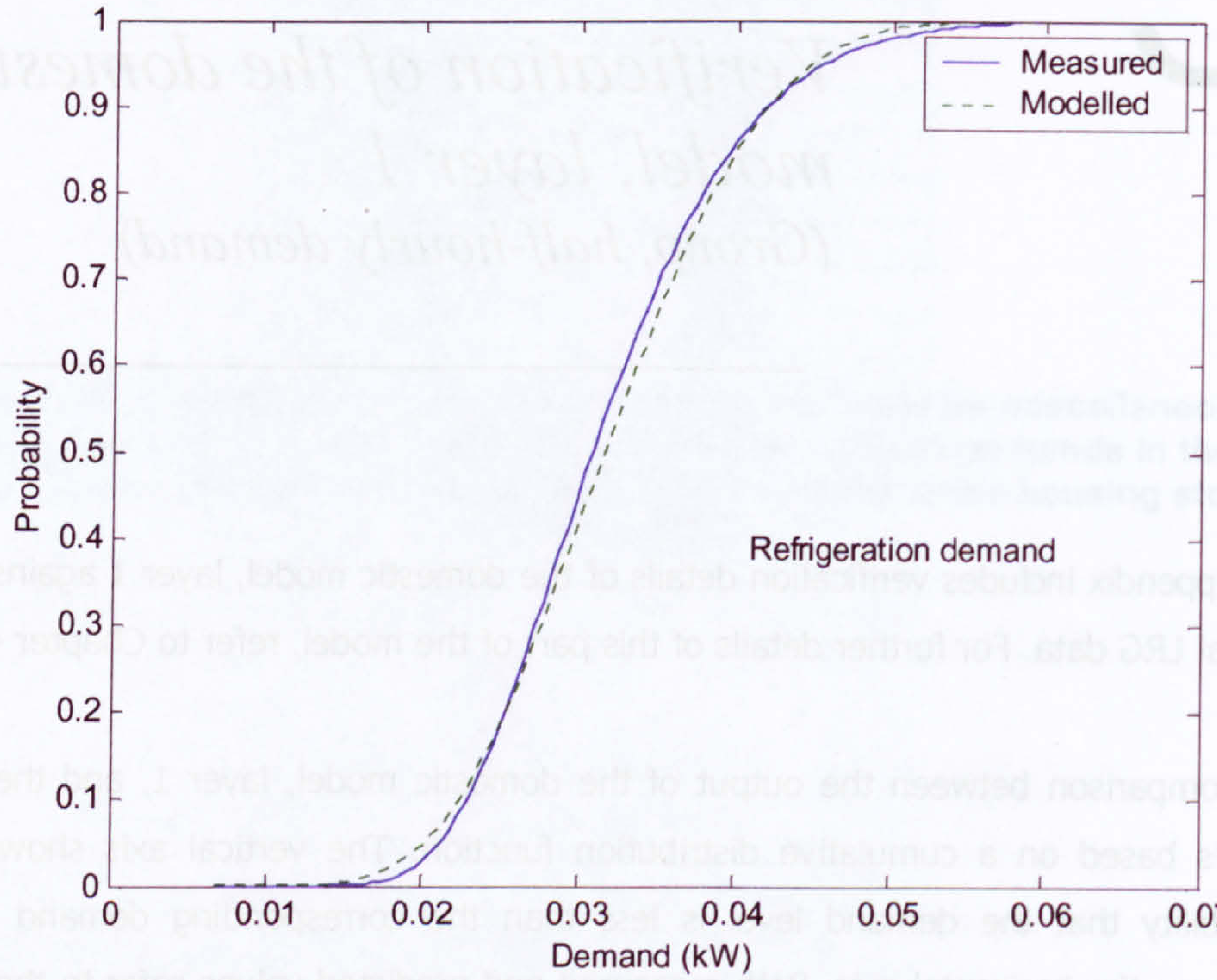


Figure C-1: Cumulative distribution function for refrigeration demand comparing LRG data against the modelled output (1996 data, group average, half-hourly)

Annual energy demand

Measured (LRG data):	282 kWh
Modelled:	282-283 kWh

Other research:

Typical annual consumption larder refrigerator [Boardman et al, 1994]:

5^{th} percentile	204 kWh
mean	270 kWh
95^{th} percentile	329 kWh

C.1.2 Freezers

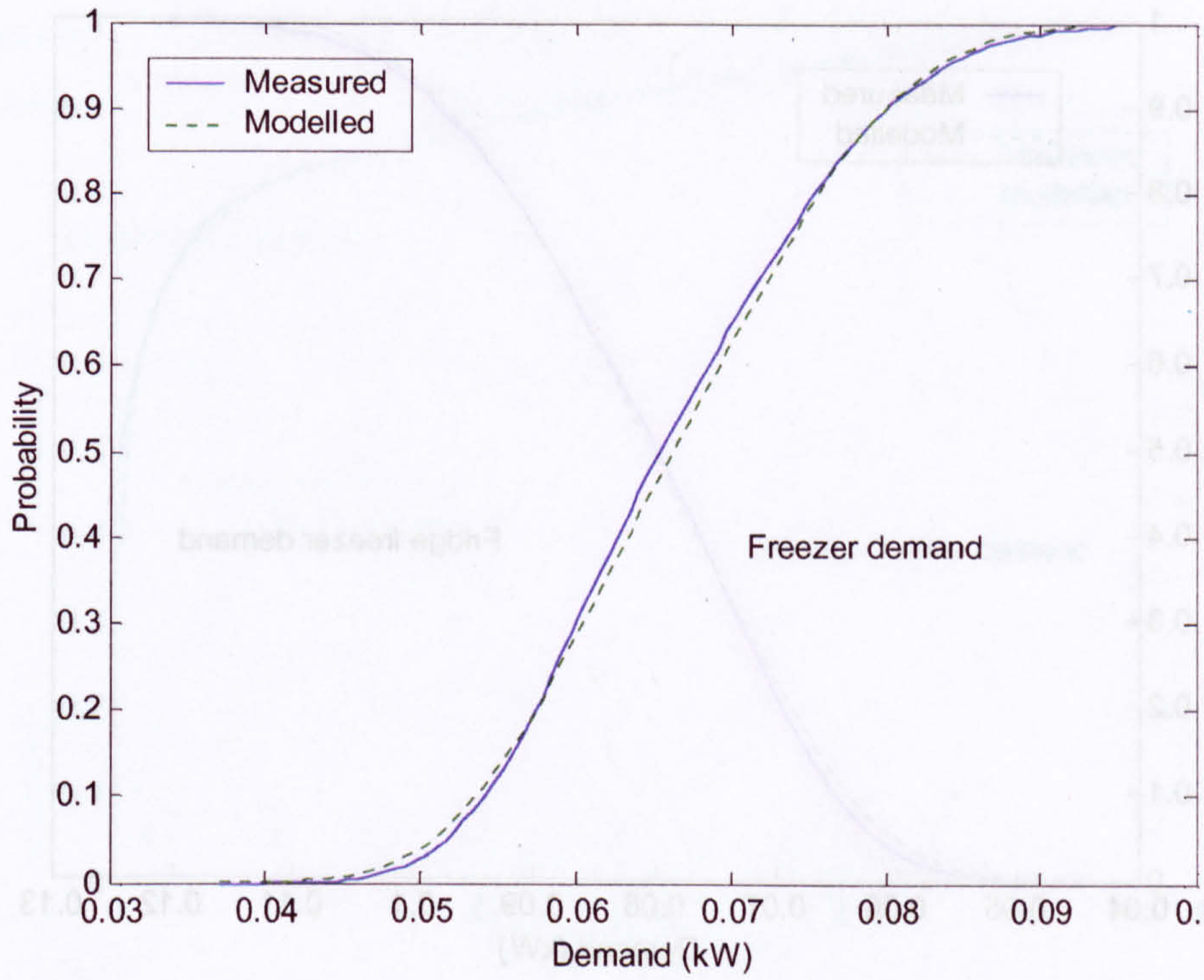


Figure C-2: Cumulative distribution function for freezer demand comparing LRG data against the modelled output (1996 data, group average, half-hourly)

Annual energy demand

Measured (LRG data):	586 kWh
Modelled:	587-588 kWh

Other research:

Typical annual consumption [Boardman et al, 1994]:

Upright freezer		Chest freezer	
5^{th} percentile	347 kWh	5^{th} percentile	292 kWh
mean	459 kWh	mean	460 kWh
95^{th} percentile	628 kWh	95^{th} percentile	589 kWh

C1.3 Fridge-freezers

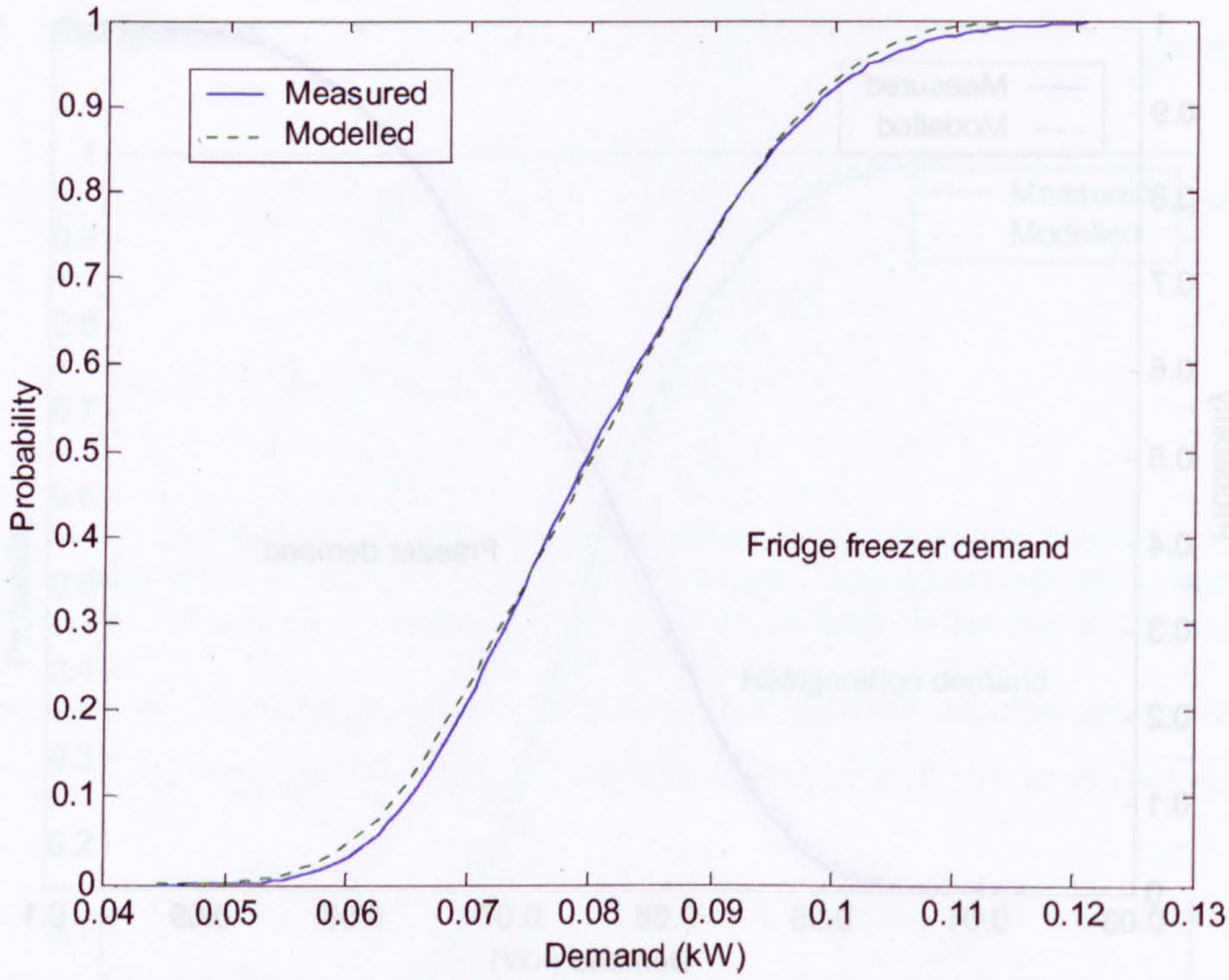


Figure C-3: Cumulative distribution function for fridge-freezer demand comparing LRG data against the modelled output (1996 data, group average, half-hourly)

Annual energy demand

Measured (LRG data):	716 kWh
Modelled:	711-713 kWh

Other research:

Typical annual consumption larder refrigerator [Boardman et al, 1994]:

5^{th} percentile	438 kWh
mean	573 kWh
95^{th} percentile	748 kWh

C.2 Space heating demand

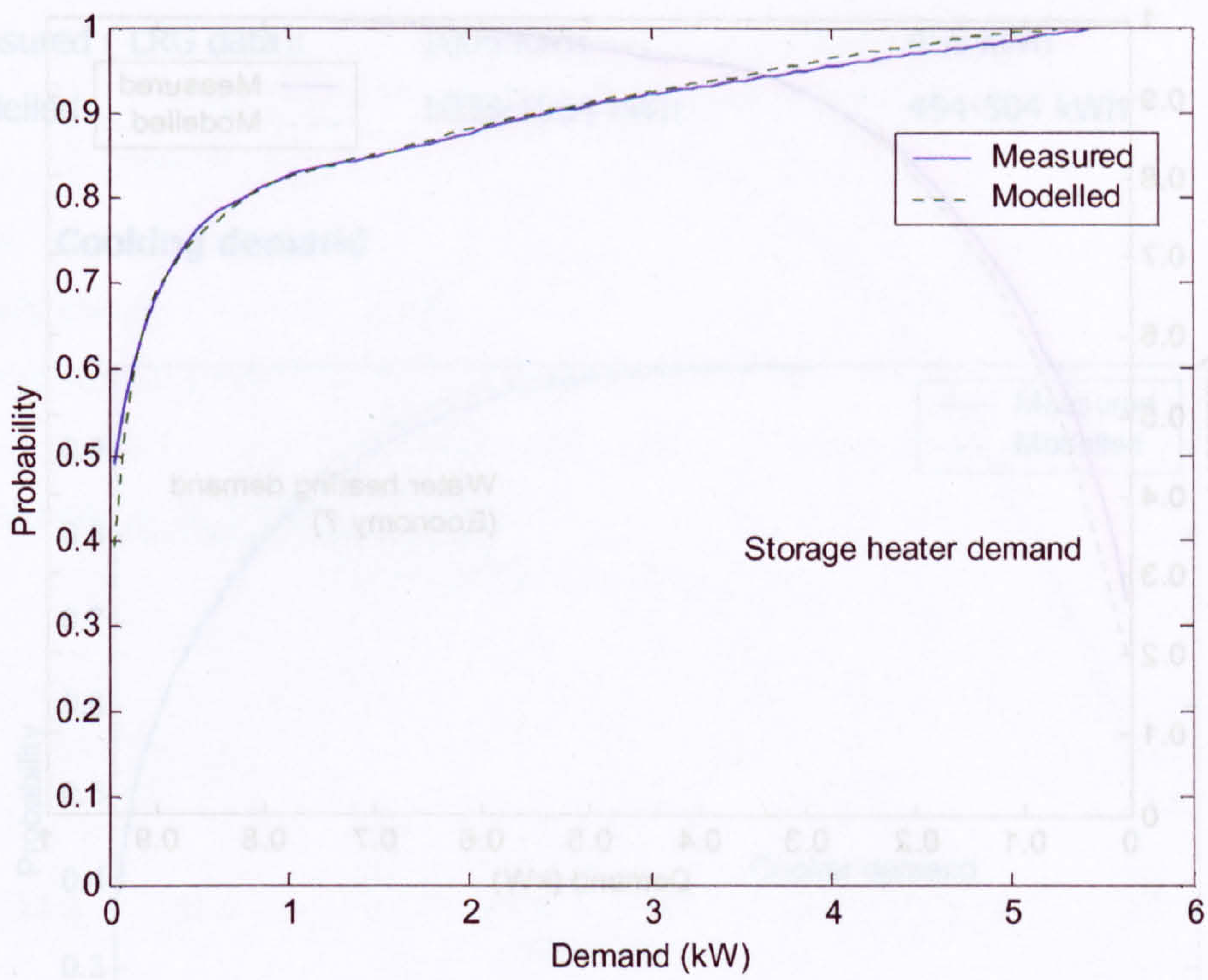


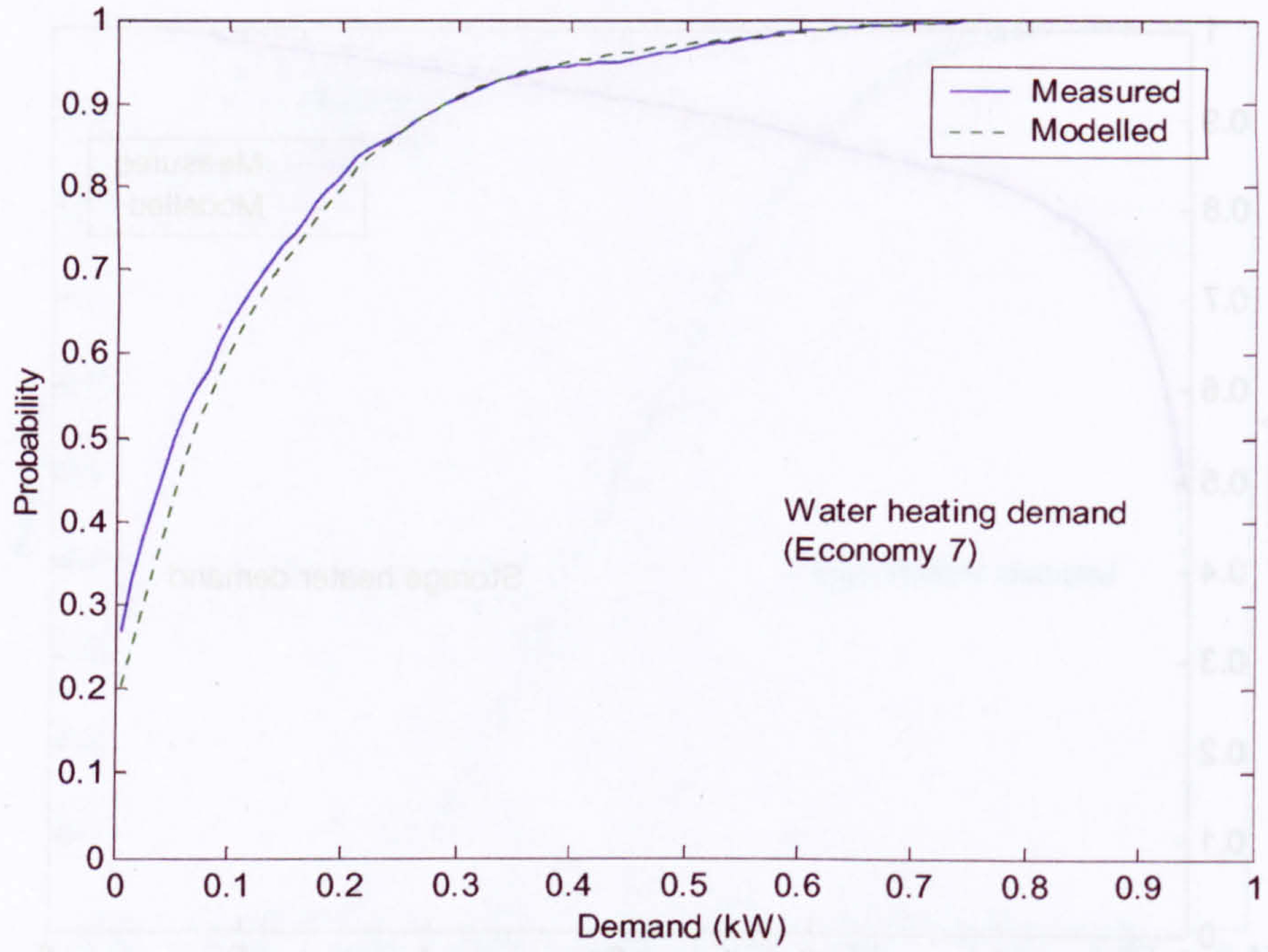
Figure C-4: Cumulative distribution function for space heating demand comparing LRG data against the modelled output (1996/7 data, group average, half-hourly)

Annual energy demand

Measured (LRG data): 5572 kWh

Modelled: 5241 - 5589 kWh

C.3 Water heating demand



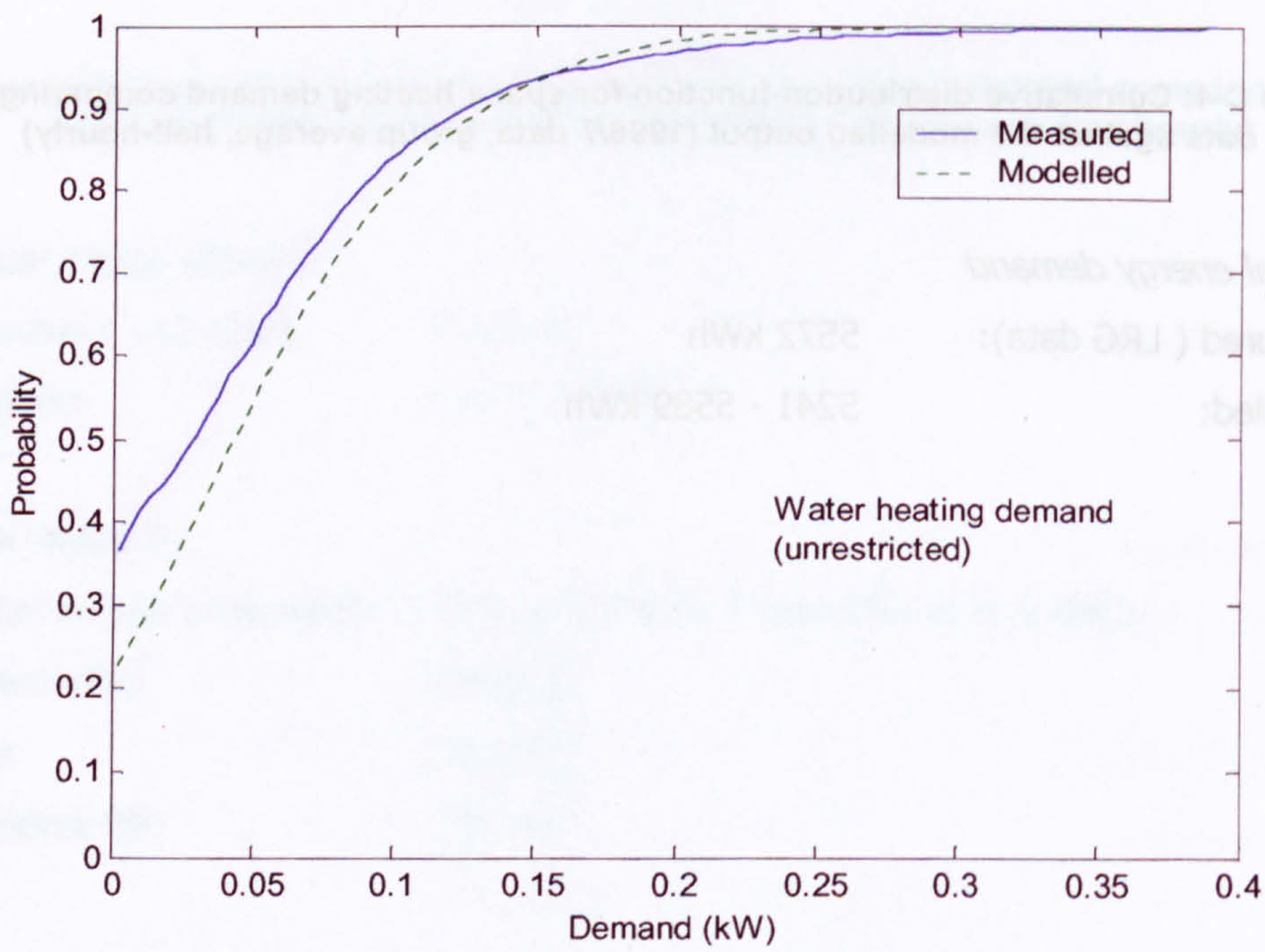


Figure C-5: Cumulative distribution function for water heating demand, for Economy 7 and unrestricted tariffs, comparing LRG data against the modelled output (1996/7 data, group average, half-hourly)

Annual energy demand

	Economy 7	*Unrestricted*
Measured (LRG data):	1006 kWh	458 kWh
Modelled:	1038-1054 kWh	494-504 kWh

C.4 Cooking demand

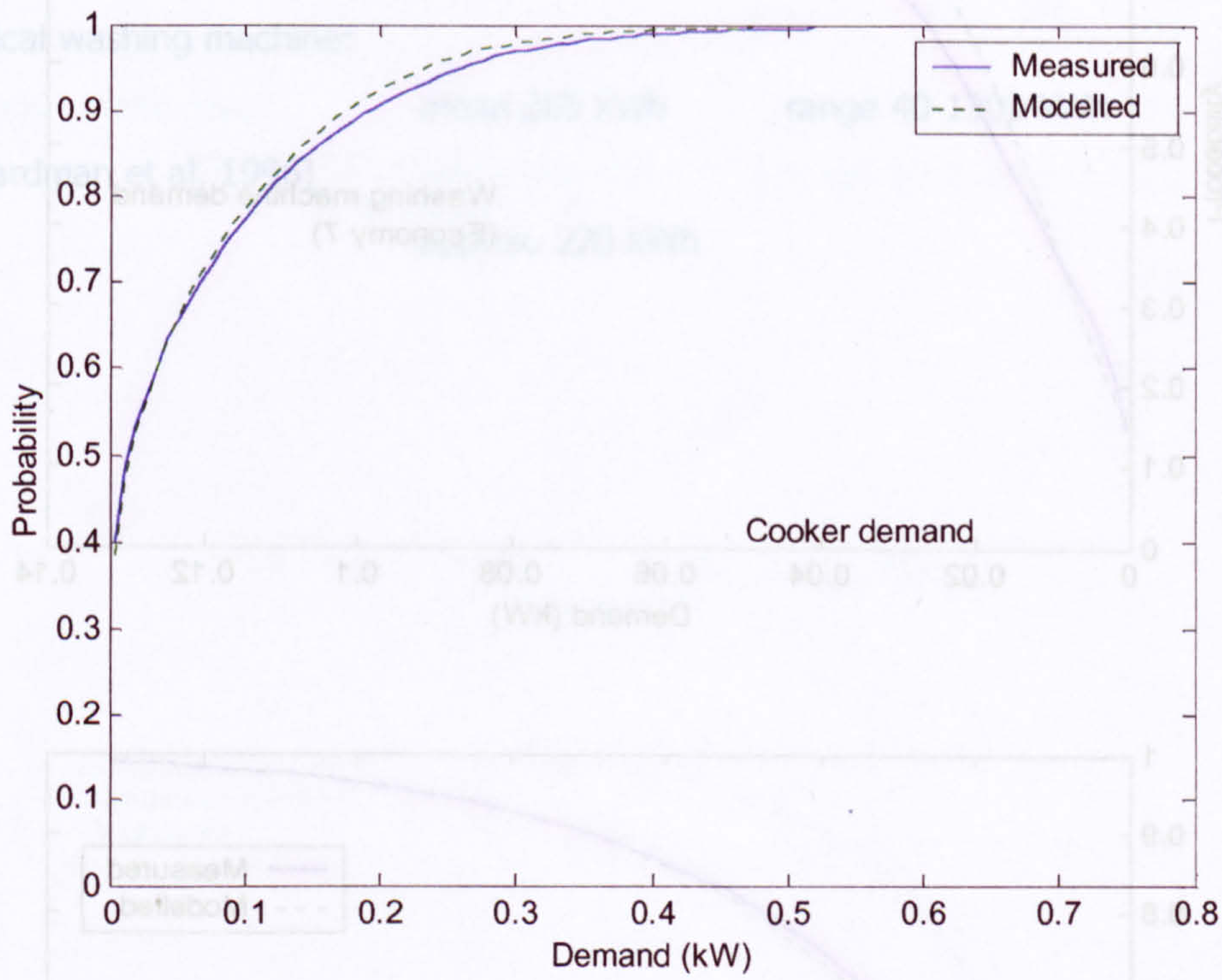


Figure C-6: Cumulative distribution function for cooking demand comparing LRG data against the modelled output (1996 data, group average, half-hourly)

Annual energy demand

Measured (LRG data):	556 kWh
Modelled:	570-578 kWh

Other research:

[Newborough & Augood, 1999]

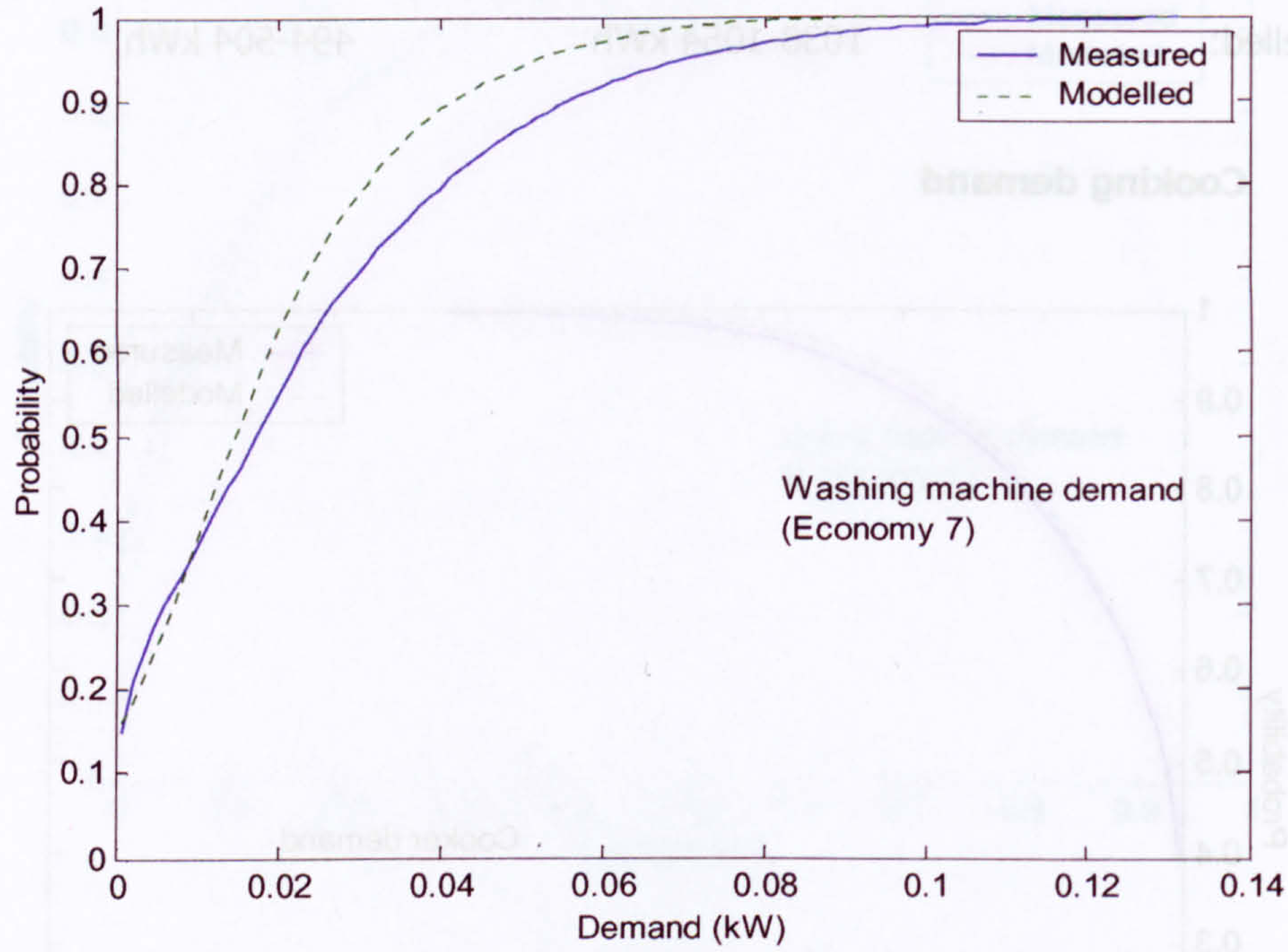
Hob:	mean 440 kWh (range 200-1200 kWh)
Oven:	mean 230 kWh (range 60-600 kWh)
Total:	mean 670 kWh

[Boardman et al, 1996]

Cooker:	664 kWh (range 20-1700 kWh)

C.5 Wet appliance demand

C.5.1 Washing machines



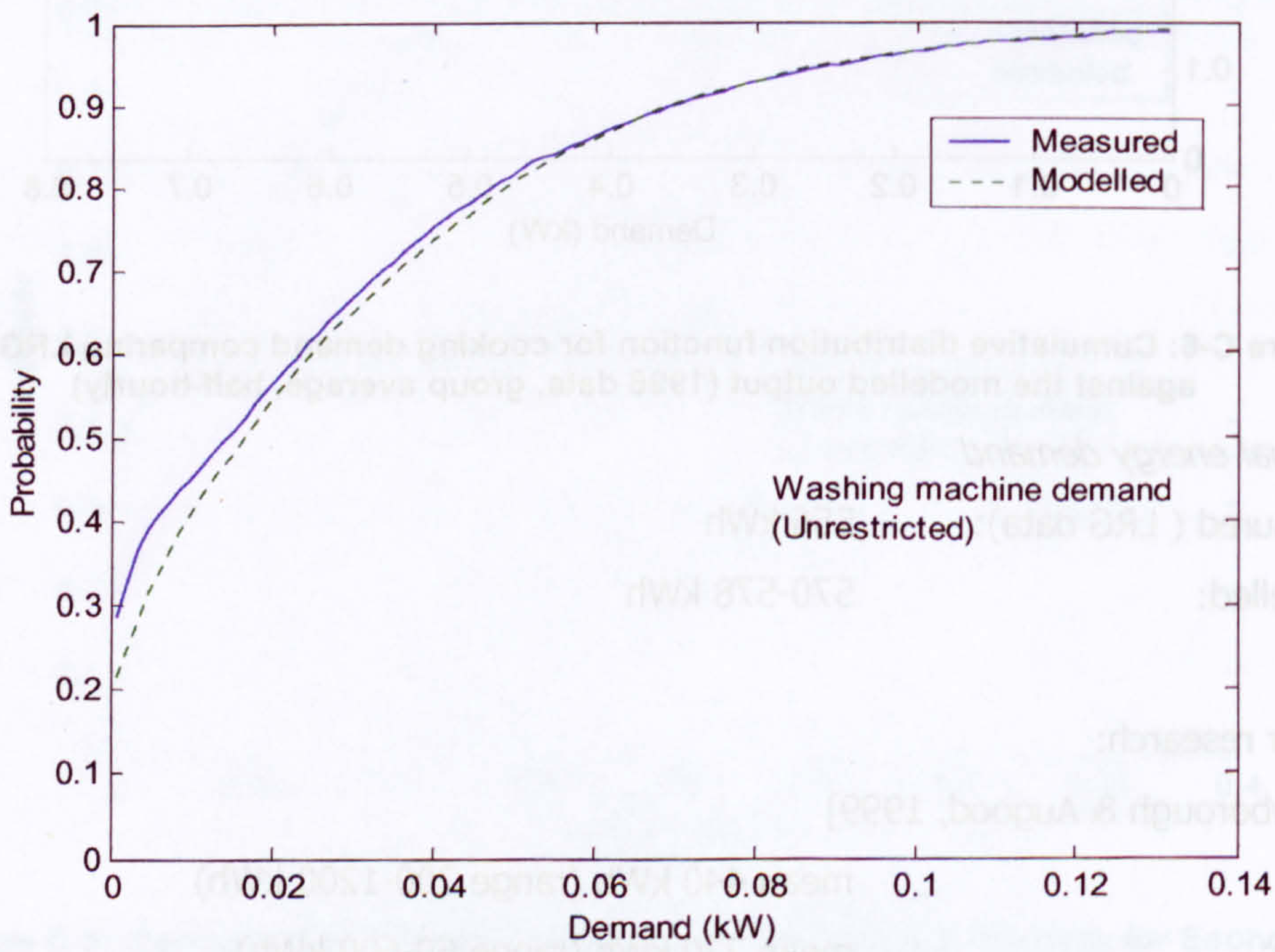


Figure C-7: Cumulative distribution function for washing machine demand, for Economy 7 and unrestricted tariffs comparing LRG data against the modelled output (1996 data, group average, half-hourly)

Annual energy demand

	Economy 7	*Unrestricted*
Measured (LRG data):	211 kWh	230 kWh
Modelled:	168-170 kWh	240-244 kWh

Other research:

[Newborough & Augood, 1999]

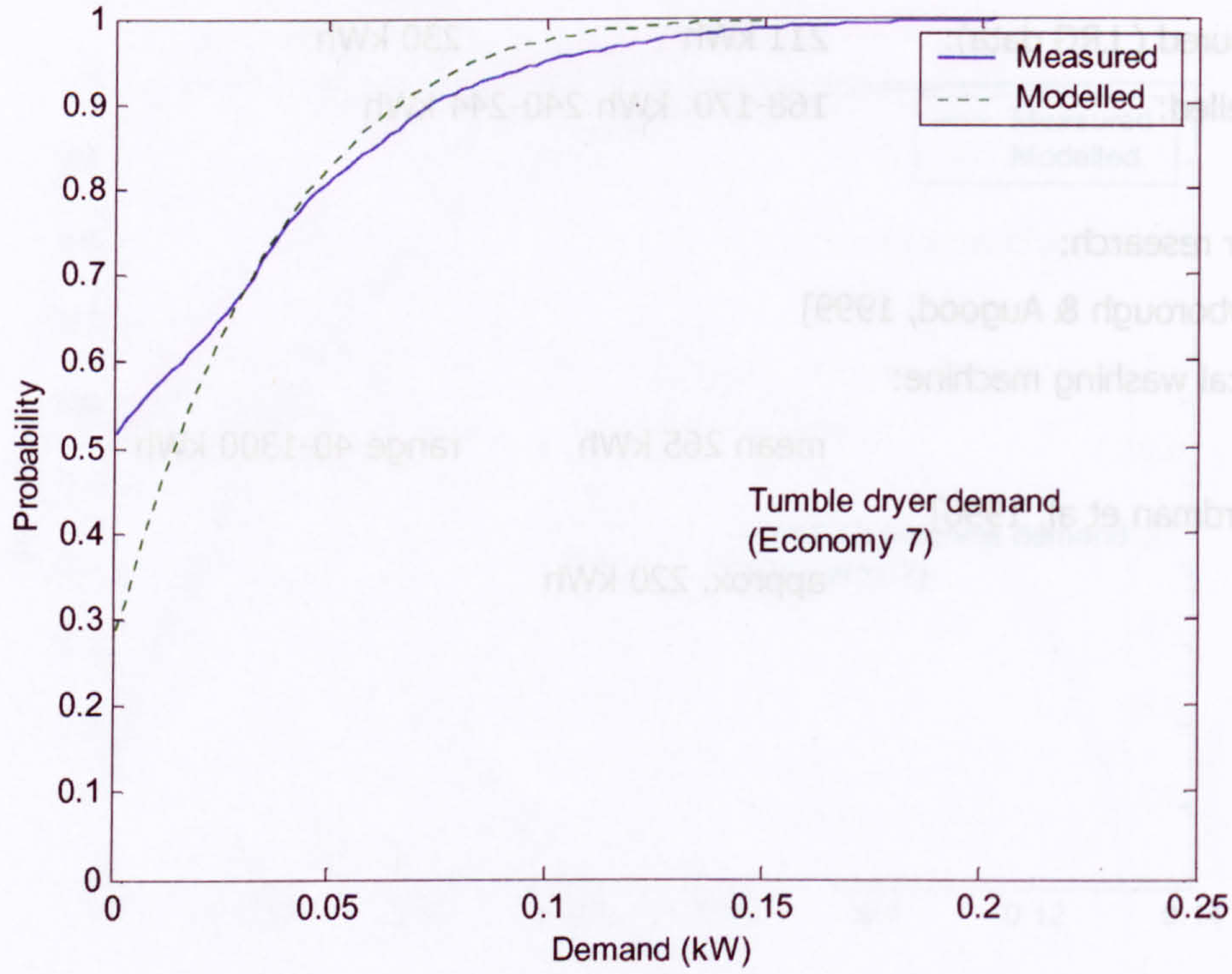
Typical washing machine:

	mean 265 kWh	range 40-1300 kWh

[Boardman et al, 1996]

approx. 220 kWh

C.5.2 Tumble dryers



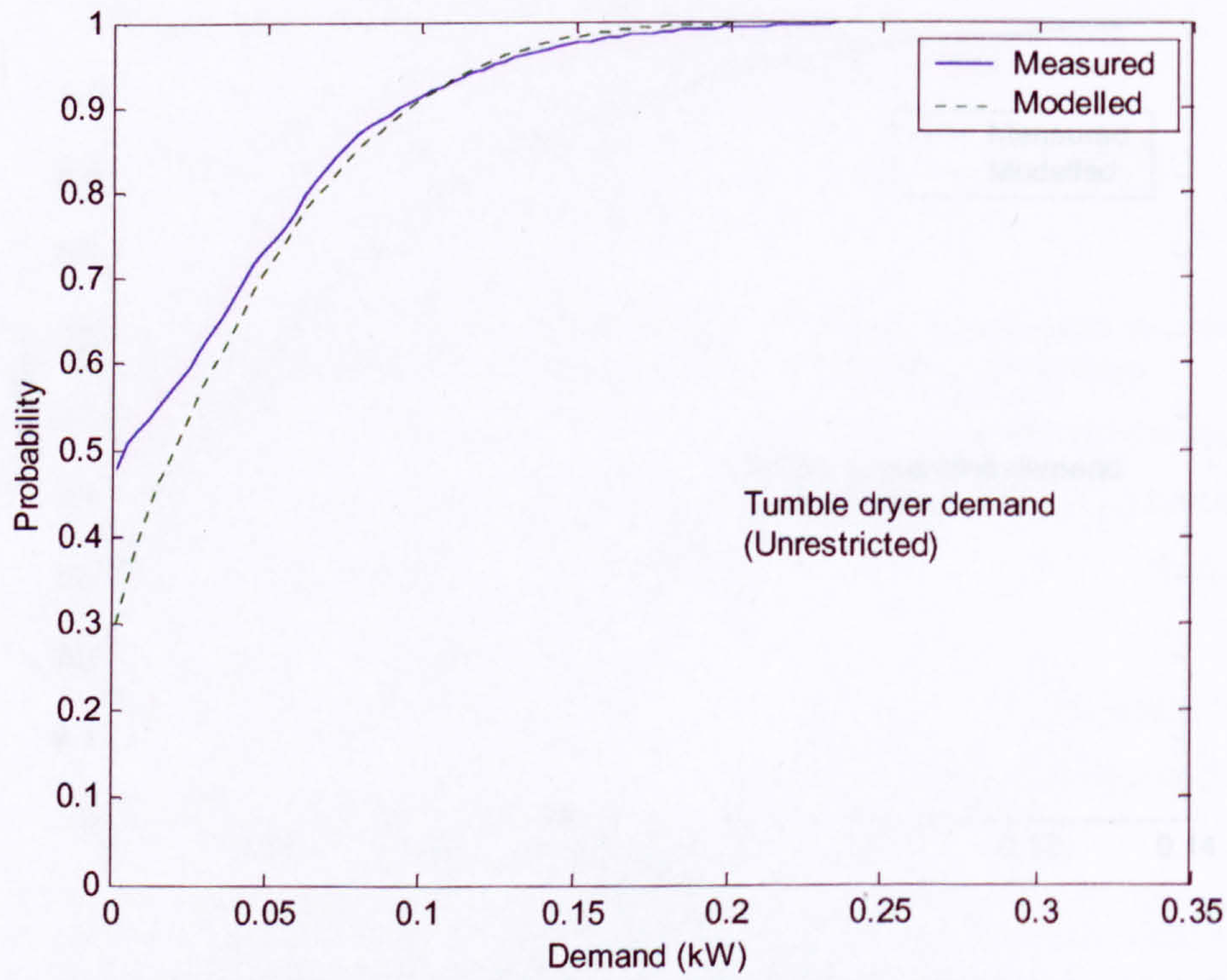


Figure C-8: Cumulative distribution function for tumble dryer demand, Economy 7 amd unrestricted tariffs, comparing LRG data against the modelled output (1996 data, group average, half-hourly)

Annual energy demand

	Economy 7	*Unrestricted*
Measured (LRG data):	218 kWh	286kWh
Modelled:	222-225 kWh	316-322 kWh

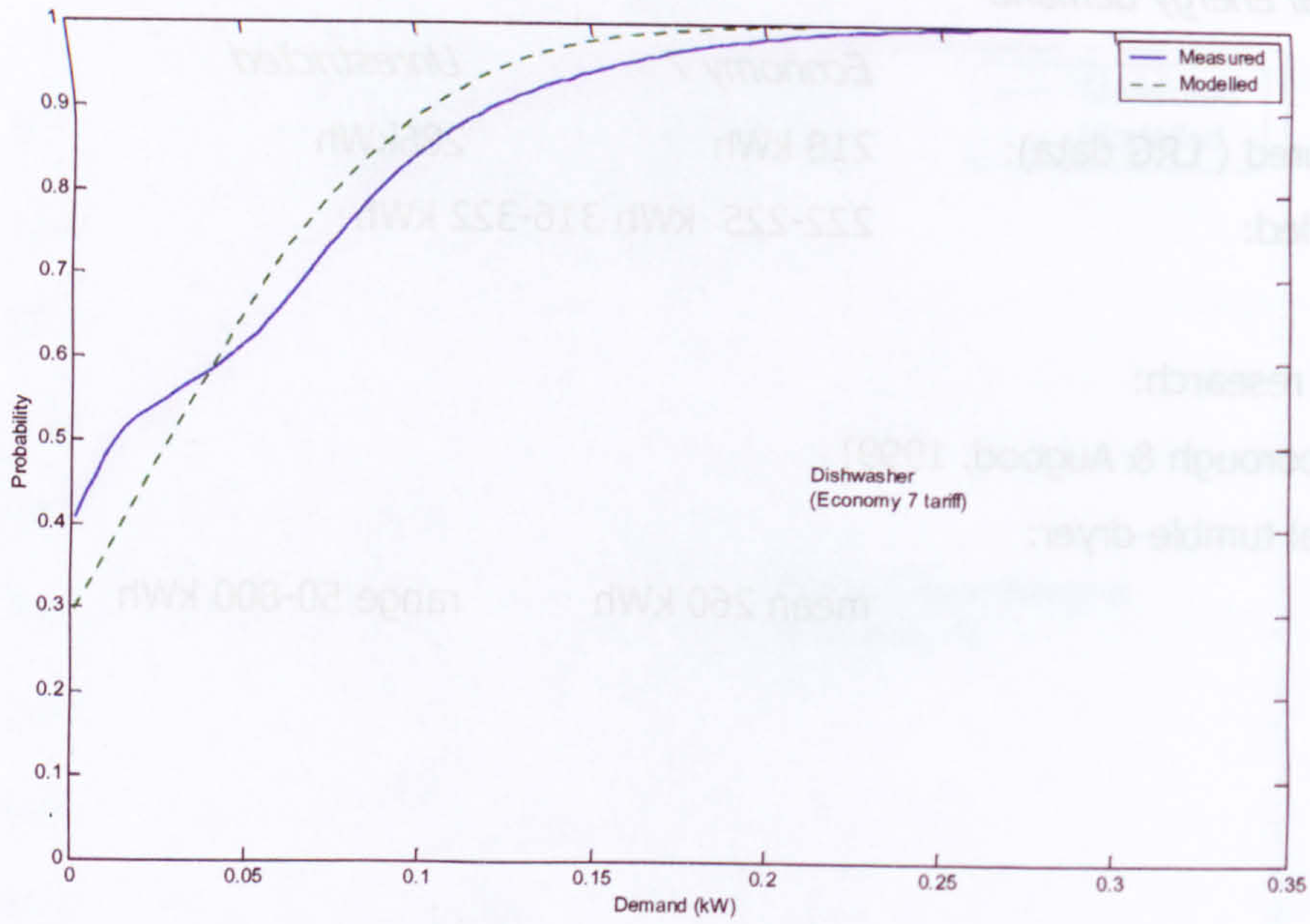
Other research:

[Newborough & Augood, 1999]

Typical tumble dryer:

	mean 260 kWh	range 50-800 kWh

C.5.3 Dishwashers



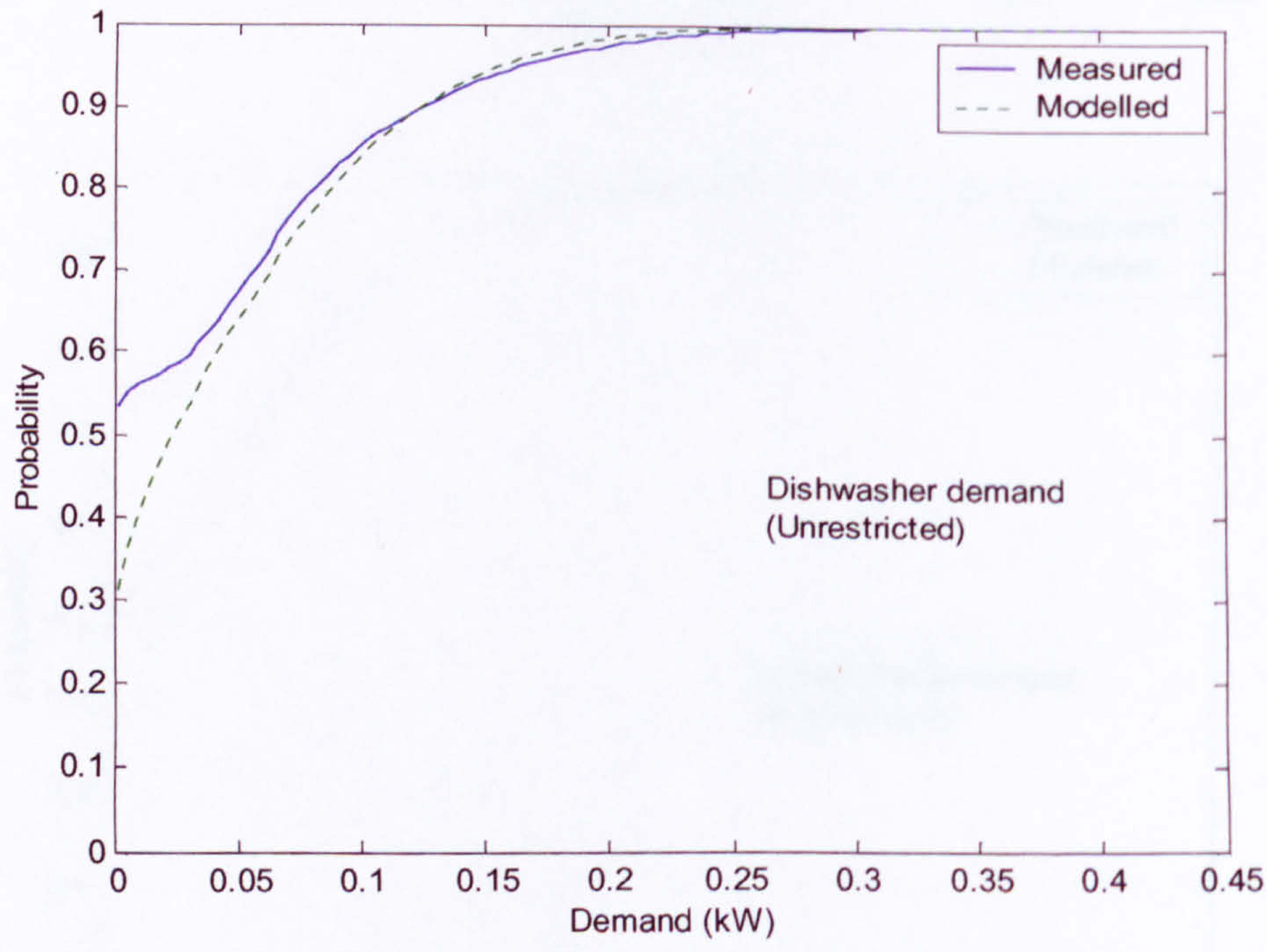


Figure C-9: Cumulative distribution function for dishwasher demand, Economy 7 and unrestricted tariffs, comparing LRG data against the modelled output (1996 data, group average, half-hourly)

Annual energy demand

	Economy 7	*Unrestricted*
Measured (LRG data):	393 kWh	364 kWh
Modelled:	360-364 kWh	405-413 kWh
Other research:		
[Newborough & Augood, 1999]		
Typical dishwasher:		
	mean 570 kWh	range 360-730 kWh

C.6 Lighting demand

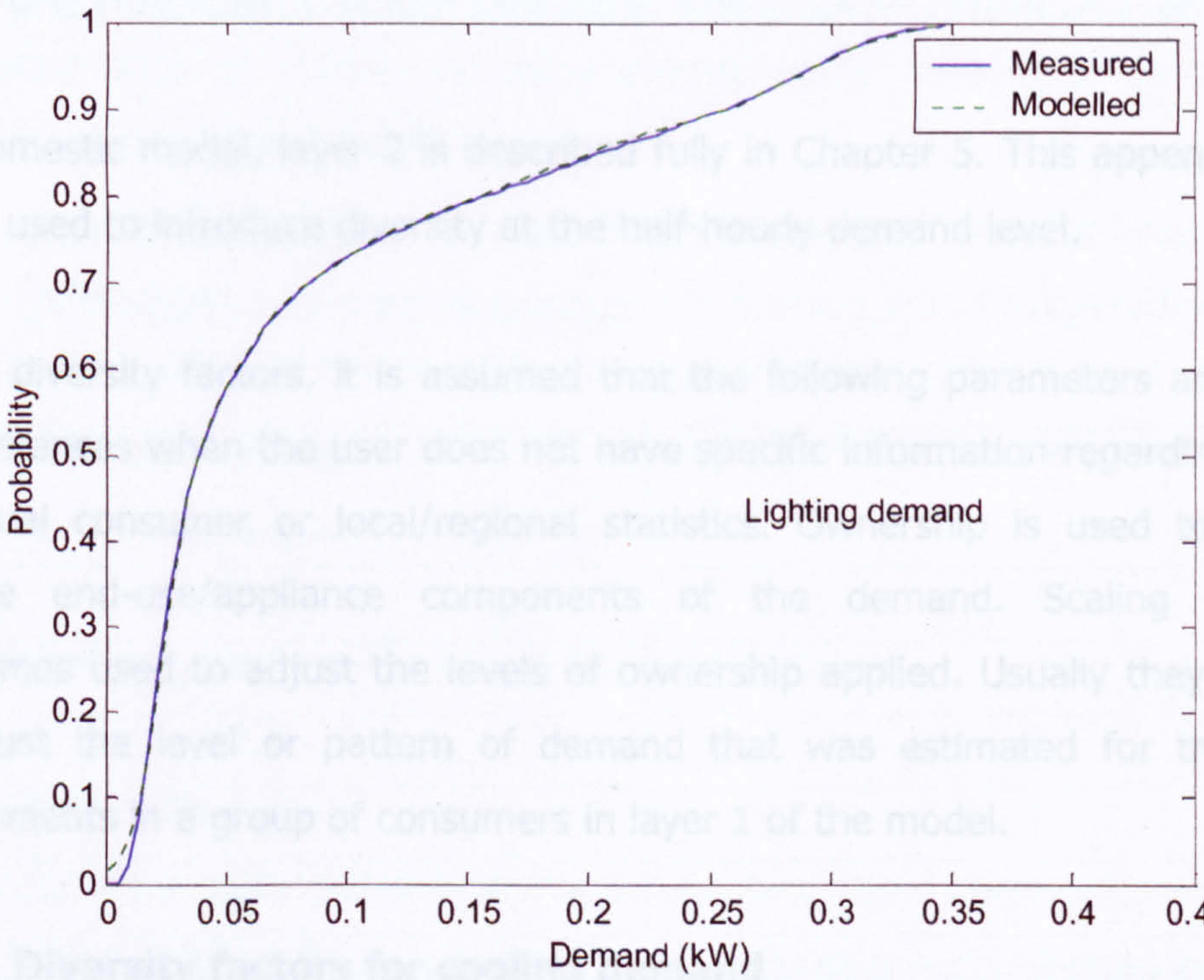


Figure C-10: Cumulative distribution function for lighting demand comparing LRG data against the modelled output (1996/7 data, group average, half-hourly)

Annual energy demand

Measured (LRG data):	758 kWh	range 625 – 875 kWh[1]
Modelled:	752-756 kWh	
Other research:		
[Newborough & Augood, 1999]		
	mean 440 kWh	range 200-1200 kWh
[Boardman et al, 1996]		
	729 kWh	

[1] The LRG report that around 80% of the lighting demand arises from the fixed lighting circuit (the remainder arising from lamps), giving an estimated average annual consumption of around 600kWh [Electricity Association, 1998(b)]. Their research suggested that lighting demand did not follow a normal distribution over the group.sampled and when simulation techniques were used to improve the fit of the distribution, there was a 90% chance that the fixed lighting demand fell within 500-700 kWh per annum.

Appendix

D

Diversity factors used in the domestic model, layer 2

(Specific, half-hourly demand)

The domestic model, layer 2 is described fully in Chapter 5. This appendix provides values used to introduce diversity at the half-hourly demand level.

For all diversity factors, it is assumed that the following parameters are applied in circumstances when the user does not have specific information regarding either the individual consumer or local/regional statistics. Ownership is used to include or exclude end-use/appliance components of the demand. Scaling factors are sometimes used to adjust the levels of ownership applied. Usually they are applied to adjust the level or pattern of demand that was estimated for the averaged requirements in a group of consumers in layer 1 of the model.

D.1 Diversity factors for cooling demand

D1.1 Ownership

Ownership of combinations of cooling appliances are assigned randomly (Table D-1). k_{own_fridge}, k_{own_ff} and $k_{own\_freezer}$ are set to either 0 or 1, depending on the comparison of a randomly generator number, between 0 and 1, to the ownership levels. For example if the number generated were less than or equal to 0.32, only a fridge-freezer would be assigned ($k_{own\_ff} = 1$, $k_{own\_fridge} = 0$, $k_{own\ freezer} = 0$). If the number is between 0.32 and 0.613, then a fridge and freezer are assigned ($k_{own\_ff} = 0$, $k_{own\_fridge} = 1$, $k_{own\ freezer} = 1$).

Appliances owned	Percentage of population
Fridge-freezer	32.0
Fridge + freezer	29.3
Fridge	8.2
Fridge + fridge-freezer	7.0
Fridge-freezer + freezer	8.4
Fridge + fridge-freezer + freezer	6.4
Fridge + 2 freezers	2.7
Fridge-freezer + 2 freezers	3.0*
Fridge + fridge-freezer + 2 freezers	2.0*
Fridge + 2 fridge-freezers + freezer	1.0*

*Assumed values (data shows 6% for 'other combinations')

Table D-1: Ownership of combinations of appliances (based on [Mansouri et al, 1996]

D1.2 Occupancy

Factors are used to scale fridge and fridge-freezer demands derived from layer 1 of the model, with regard to the number of occupants in the house (Table D-2).

Number of occupants	Scaling factor ($k_{occ\_fridge}, k_{occ\_ff}$)
1	0.59
2	0.88
3	1.18
4	1.24
5 or more	1.25

Table D-2: Scaling factors based on occupancy for fridge and fridge-freezer demand (based on LRG data [Electricity Association, 1998], Figure 2.7)

For freezers, the scaling factor ($k_{occ\_freezer}$) is determined randomly from a Gaussian distribution, with a mean value of zero and a standard deviation of 0.316 (based on limited survey of retailed appliances).

D.2 Diversity factors for space heating demand

D2.1 Ownership

Within the group of consumers assigned an off-peak tariff, 10% are also randomly assigned electric space storage heating and also if the user indicates that the area/building is not supplied with gas (based on MTP data [DEFRA, 2001]). The space heating ownership factor, k_{own_heat} is set to 1 if ownership is assigned and 0 if not.

(Use of an off-peak tariffs is either assigned using specific knowledge or randomly. If electric space heating is assigned, it is assumed that a consumer will be using an off-peak tariff. For the model it has also been assumed that a further 16% of consumers use an off-peak tariff (taken from MTP data [DEFRA, 2001] and based on the assumption that all consumers using electric water heating in winter also buy electricity on an off-peak tariff).

D2.2 Living space

Space heating demand is scaled (factor k_{occ_heat}) by the ratio of the total floor area (i.e. living space in m^2) to an averaged value of $87m^2$ [ODPM, 2001].

D.3 Diversity factors for water heating demand

D3.1 Ownership

The model assigns ownership of immersion heaters based on annual trends and built form (Tables D-3 and D-4). A probability of ownership is determined by multiplying the ownership values of column 2 of Table D-3 with the appropriate built-form weighting factors of Table D-4. A random number, between 0-1, is generated on a linear basis. If less than or equal to the probability of ownership, k_{own_water} is set to 1. Within this group with ownership of an immersion heater, the same process is used to determine all-year round use (using column 3 of Table D-3, k_{own_water} remains = 1), summer only use (using column 4 of Table D-3, k_{own_water} = 1 during June-September inclusive, = 0 at all other times), non-use (k_{own_water} =0).

Year	Ownership % population	All year use % owning	Summer use % owning
1970	60	74.0	14.5
1975	65	68.0	16.0
1980	67	53.5	15.1
1985	67	43.3	14.9
1990	66	33.1	14.8
1995	64	27.3	14.8
1998	63	26.2	14.8
2000	63	25.8	14.9
2005	61	25.7	14.9
2010	60	25.2	14.9
2015	58	24.6	14.9
2020	57	23.9	14.9

Table D-3: Ownership trends for immersion heater ownership and corresponding use all year round or summer only (based on MTP data [DEFRA, 2001])

D3.2 Tariff

All consumers already assigned off-peak space heating (10% of group if randomly assigned, k_{own_heat} = 1) are also assigned off-peak all year round water heating (k_{own_water} = 1). The remaining proportion of potential immersion heater users is distributed randomly (for the group as a whole, 26% are randomly assigned an off-peak tariff, unless specific information is supplied by the user, including the 10% with electrical space heating).

D3.3 Ownership and built form

Scaling factors are applied to ownership based on year of construction and built form (Table D-4).

Built form and age	Scaling factor for distribution of use of water heating by electric
Detached house: pre-1919	1.00
Detached house: post 1919	1.03
Semi-detached & terraced: pre 1919	0.83
Semi-det. & terraced : 1919 – 1944	0.89
Semi-detached & terraced: 1945 – 1964	1.03
Semi-detached and Terraced : post 1965	1.06
Bungalows	1.15

Table D-4: Scaling factor for assigning users of water heating based on built form (based on [Gadsden, 2001]

D3.4 Occupancy

Scaling factors are used to weight the water heating demand according to the number of occupants in a household (Table D-5).

Number of occupants	Scaling factor (k_{occ_water})
1	0.6
2	0.9
3	1.2
4	1.4
5	1.7
6	1.9
7 or more	2.2

Table D-5: Scaling factor for water heating demand based on occupancy (based on BREDEM-8 model [Shorrock et al, 1991])

D3.5 General levels of demand

In the BREDEM-8 model water heating energy demand is scaled by a factor depending on whether demand for hot water is described as high, average, low or very low. For the model, the selection is made randomly using an assumed distribution (Table D-6).

Description of hot water usage	Scaling factor ($k_{hi\text{-}lo\_water}$)	Percentage of population (%)
High	1.2	11
Average	1.0	75
Low	0.8	12
Very low	0.6	2

Table D-6: Scaling factor for water heating demand based on variations in use of hot water (based on an assumed distribution)

D.4 Diversity factors for cooking demand

D4.1 Ownership trends

Consumers assigned electric space heating are assumed to use electric hobs and ovens. Ownership of ovens and hobs is assigned randomly using the trend data (Table D-7). Consumers assigned an electric hob are also assigned an electric oven.

Year	Ownership of electric hobs %	Ownership of electric ovens
1970	42	42
1980	43	44
1990	47	53
2000	48	68
2010	46	64
2020	42	69

Table D-7: Trends in ownership of electric hobs and ovens (based on MTP data [DEFRA, 2001])

Ownership of kettles is applied randomly at a level of 98% ownership and for microwaves at 85% ownership.

D4.2 Ownership and lifestyle

Ownership of microwaves is varied according to the lifestyle category (Table D-8).

ACORN lifestyle category	Ownership scaling factor
A	1.01
B	1.01
C	0.95
D	1.19
E	0.87
F	0.90

Table D-8: Scaling factor applied to microwave ownership depending on ACORN lifestyle category (based on [Mansouri et al, 1996])

D4.3 Occupancy

Scaling factors are applied to demand associated with the four cooking appliances depending on the number of occupants in the household (Table D-9).

Number of occupants	Scaling factor k_{occ_cook}
1	0.53
2	0.93
3	1.07
4 or more	1.08

Table D-9: Scaling factor for cooking demands based on occupancy (based on DECADE data [Boardman et al, 1994])

D.5 Diversity factors for wet appliance demand

D5.1 Ownership

The trends in ownership for wet appliances are applied randomly over the network area (Table D-10). 15% of owners assigned with a washer-dryer appliance are also assigned a tumble dryer. Other combinations of ownership occur randomly.

Year	Ownership, % of population			
	Washing machines	Tumble dryers	Dishwashers	Washer-dryers
1970	64	7	1	0
1975	71	6	4	1
1980	77	17	5	5
1985	79	28	6	12
1990	77	35	13	15
1995	76	35	19	15
1998	76	35	22	15
2000	76	35	24	15
2005	77	34	27	15
2010	78	34	29	15
2015	78	35	30	15
2020	79	35	31	15

Table D-10: Trends in ownership of wet appliances (based on MTP data [DEFRA, 2001])

D5.2 Ownership and lifestyle

Ownership is adjusted for ACORN lifestyle category by scaling the ownership values for washing machines, tumble dryers and dishwashers (Table D-11).

ACORN lifestyle category	Ownership scaling factor		
	Washing machine	Tumble dryer	Dishwasher
A	1.01	0.98	1.33
B	1.01	0.98	1.33
C	0.96	0.89	0.81
D	1.04	1.29	1.12
E	0.98	1.15	0.86
F	0.98	0.82	0.84

Table D-11: Scaling factors for adjusting levels of ownership of wet appliances based on ACORN lifestyle category (based on [Mansouri et al, 1996])

D5.3 Tariff

Consumers are either linked to off-peak or unrestricted tariff demands depending on which tariff has already been assigned (assumed 26% are on off-peak tariffs, of which 10% are using storage heating).

D5.4 Occupancy

Weighting factors are applied to scale the demand assigned for all types of wet appliance depending on the number of occupants (Table D-12).

Number of occupants	Scaling factor k_{occ_wet}
1	0.55
2	0.81
3	1.28
4	1.55
5	1.69
6 or more	2.14

Table D-12: Scaling factor for adjusting demand from wet appliances in relation to occupancy (based on [Mansouri et al, 1996])

D5.5 Demand level and lifestyle

The demand for washing machines, tumble dryers and washer-dryers is scaled according to ACORN lifestyle category (Table D-13, no scaling is used for dishwasher demand).

ACORN lifestyle factor	Demand scaling factor $k_{lifestyle\_wet}$	
	Washing machine	Tumble dryer
A	0.93	1.04
B	0.93	1.04
C	0.81	0.76
D	1.36	1.18
E	1.24	1.99
F	1.10	0.76

Table D-13: Scaling factor for adjusting demand from washing machine sand dryers in relation to ACORN lifestyle category (based on [Mansouri et al, 1996])

D.6 Diversity factors for lighting and miscellaneous demand

D6.1 Occupancy

Both lighting and miscellaneous demands are adjusted in terms of the daily pattern depending on the number of occupants in a household (Table D-14).

Half Hour Ref.	Scaling factor based on number of occupants $k_{occ\ lights(I,J)}$			
	1	2	3	4 or more
1	1.02	0.66	0.561	1.224
2	0.73	0.44	0.439	1.171
3	0.58	0.52	0.520	1.349
4	0.41	0.41	0.478	1.555
5	0.42	0.42	0.507	1.494
6	0.45	0.45	0.549	1.615
7	0.48	0.48	0.630	1.741
8	0.40	0.48	0.595	1.587
9	0.34	0.42	0.634	1.479
10	0.36	0.49	0.670	1.339
11	0.42	0.84	0.844	1.266
12	0.74	0.82	0.817	1.300
13	0.73	0.73	0.732	1.464
14	0.50	0.74	0.745	1.655
15	0.44	0.74	0.745	1.397
16	0.43	0.72	0.859	1.397
17	0.39	0.74	0.967	1.354
18	0.48	0.90	1.200	1.200
19	0.50	0.93	1.262	1.009
20	0.53	0.79	0.986	1.000
21	0.58	0.78	1.005	1.005
22	0.61	0.66	0.979	1.000
23	0.65	0.65	1.039	1.039
24	0.67	0.67	1.075	1.075
25	0.66	0.68	1.067	1.121
26	0.65	0.68	1.000	1.135
27	0.62	0.62	0.931	1.164
28	0.61	0.63	0.884	1.187
29	0.58	0.63	0.903	1.255
30	0.61	0.63	0.896	1.187
31	0.56	0.56	1.000	0.929
32	0.67	0.67	1.348	1.348
33	0.57	0.65	1.310	1.528
34	0.67	0.85	1.279	1.401
35	0.69	0.88	1.203	1.342
36	0.74	0.93	1.168	1.285
37	0.71	0.90	1.113	1.252
38	0.72	0.86	1.094	1.208
39	0.71	0.81	1.093	1.173
40	0.73	0.82	0.984	1.180
41	0.73	0.84	0.935	1.186
42	0.74	0.86	0.925	1.201
43	0.75	0.88	0.938	1.203
44	0.74	0.89	0.958	1.170
45	0.78	0.87	0.959	1.129
46	0.85	0.85	0.853	1.088
47	0.90	0.79	0.791	1.159
48	0.97	0.83	0.798	1.284

Table D-14: Scaling factors for adjusting the daily profile of lighting and miscellaneous demand, in relation to occupancy (based on LRG data, [Electricity Association, 1998(b)])

D6.2 Demand level and lifestyle

Similarly, lighting and miscellaneous demand are adjusted with regard to lifestyle category (unless specific income information is available, Table D-15).

Half Hour Ref.	Scaling factor based on ACORN category $k_{lifestyle\_lights(I,J)}$			
	A	B & C	D & E	F
1	0.87	0.87	0.867	1.224
2	0.73	0.73	0.732	1.390
3	0.67	0.87	0.675	1.446
4	0.72	1.08	0.717	1.435
5	0.79	1.13	0.705	1.410
6	0.65	1.29	0.646	1.453
7	0.74	1.30	0.741	1.482
8	0.87	1.31	0.873	1.388
9	0.89	1.27	0.972	1.479
10	0.89	1.21	1.116	1.652
11	1.01	1.14	1.139	1.603
12	0.93	1.00	1.374	1.448
13	0.88	0.88	1.171	1.464
14	0.83	0.83	1.655	0.993
15	1.12	0.93	1.304	0.838
16	1.11	1.04	1.110	0.716
17	1.08	1.39	1.083	0.696
18	0.96	1.56	0.960	0.840
19	0.87	1.35	0.875	0.875
20	0.93	1.38	0.986	1.005
21	1.01	1.45	1.005	1.117
22	0.98	1.27	0.979	1.150
23	0.96	1.30	0.961	1.195
24	1.05	1.34	0.968	1.210
25	1.15	1.31	0.957	1.203
26	1.16	1.22	0.946	1.162
27	1.19	1.24	1.008	1.138
28	1.16	1.26	1.011	1.162
29	1.13	1.25	1.029	1.204
30	1.14	1.33	1.066	1.211
31	1.03	1.28	1.032	1.156
32	1.06	1.42	1.064	1.206
33	1.05	1.31	1.048	1.048
34	0.94	1.22	1.157	0.944
35	1.04	1.06	1.157	0.925
36	1.07	1.07	1.187	0.876
37	1.08	1.08	1.182	0.876
38	1.08	1.08	1.159	0.882
39	1.09	1.08	1.125	0.842
40	1.12	1.08	1.108	0.836
41	1.10	1.04	1.129	0.835
42	1.11	1.01	1.117	0.841
43	1.13	1.01	1.134	0.849
44	1.10	0.99	1.107	0.869
45	1.11	0.98	1.016	0.847
46	1.07	0.98	0.960	0.853
47	1.05	0.97	0.922	0.922
48	1.01	1.01	1.006	1.006

Table D-15: Scaling factors for adjusting the daily profile of lighting and miscellaneous demand, in relation to ACORN lifestyle catgeory (based on LRG data, [Electricity Association, 1998(b)])

D6.3 Income

Where specific income information scaling factors related to income are used in place of those related to lifestyle category (Table D-16).

Half Hour ref.	Scaling factors based on income $k_{income\ lights}$	
	Below national average	Above national average
1	1.02	0.97
2	1.17	0.99
3	1.06	0.93
4	1.12	1.00
5	1.13	0.99
6	1.00	0.81
7	1.00	0.81
8	0.99	0.87
9	1.01	0.97
10	1.00	0.98
11	1.00	1.00
12	0.93	1.00
13	0.76	1.02
14	0.50	1.24
15	0.56	1.44
16	0.57	1.43
17	0.58	1.35
18	0.66	1.44
19	0.67	1.01
20	0.69	1.01
21	0.74	1.05
22	0.73	1.10
23	0.78	1.12
24	0.81	1.10
25	0.79	1.12
26	0.81	1.16
27	0.72	1.16
28	0.83	1.09
29	0.88	1.05
30	0.85	1.02
31	0.93	0.99
32	0.71	1.06
33	0.61	1.05
34	0.61	1.07
35	0.69	1.02
36	0.78	1.17
37	0.78	1.22
38	0.74	1.22
39	0.73	1.22
40	0.74	1.21
41	0.75	1.20
42	0.75	1.13
43	0.77	1.12
44	0.76	1.10
45	0.78	1.02
46	0.83	1.00
47	0.97	1.00
48	1.00	1.00

Table D-16: Scaling factors for adjusting the daily profile of lighting and miscellaneous demand, in relation to income (based on LRG data, [Electricity Association, 1998(b)])

Consumers with a total household income at the national average are assigned un-scaled demands for lighting and miscellaneous demand.

D.7 Power factors

Power factors are used to determine the reactive component of the total demand (Table D-17).

Appliance/end-use	Assumed power factor (cos φ)
Cooling appliances	0.7
Space heating	1.0
Water heating	1.0
Cooking appliances	1.0
Wet appliances Washing machine* Tumble dryer Dishwasher	 0.93 0.98 1.0
Lighting	1.0
Miscellaneous appliances	1.0

*washer dryer demand uses a split value depending on whether the load is from washing or drying

Table D-17: Power factors associated with various appliance/end-use demands (based on [Newborough & Augood, 1999])

Appendix

E

Values for factors used in the domestic model, layer 3
(Specific, one-minute demand)

The following values are used to introduce further diversity into the domestic model and to calculate 1-minute averaged demands from half-hourly assigned demands (as detailed in Chapter 6).

E.1 Factors for cooling demand – layer 3

E1.1 Scale

Cooling events occur at the same level of demand throughout. The scale of demand is determined by the appliance rating. Refrigerators are sized with a mean value of 0.060 kW and scaled according to the occupancy, as described in Appendix D, section D1.2. Similarly, fridge-freezers are assumed to have a mean rating of 0.120 kW and are scaled by an occupancy factor. Freezers are assumed to have a rating selected randomly with a normal distribution, of mean 0.093 kW and standard deviation of 0.020 kW.
(Parameter values based on a limited survey of currently retailed cold appliances).

E1.2 Timing

The event duration is determined by dividing the assigned half-hourly demand by the selected appliance rating (multiplied by 30 to give the number of minutes). The start time is selected randomly such that the event is completed within the current half-hour.

E1.3 Frequency

It is assumed that, unless the assigned demand in the current half-hour is zero, one event occurs every half-hour.

E1.4 Triggering

An event is triggered if the assigned cooling demand is greater than zero.

E1.5 Power factor

A power factor of 0.7 is assumed for all cold appliance events [Newborough & Augood, 1999].

E.2 Factors for space heating demand – layer 3

E2.1 Scale

The rating of the heating demand is given by the maximum half-hourly assigned demand that occurs up to 08:30 on a given day. Until the half-hour in which this maximum value occurs, the scale of the event is adjusted to match the half-hourly assigned demand. In the half-hour in which the maximum demand occurs until 08:30, the demand events occur at the maximum level. Between 08:30 until 23:59, the level of demand is again set equal to the assigned half-hourly demand.

E2.2 Timing

Up to and including the half-hour when maximum demand occurs, heating events are assumed to run continuously throughout the half-hour. After the maximum demand is reached, the duration of the event is given by dividing the assigned half-hourly demand by the maximum demand (multiplied by 30 minutes). The event has a random start time, with the event being completed within the current half-hour. From 08:30, the demand is again assumed to run continuously throughout the half-hour.

E2.3 Frequency

If the assigned heating demand in a given half-hour is greater than zero, a single heating event will occur within that half-hour.

E2.4 Triggering

If a non-zero half-hourly heating demand is assigned, an event will automatically occur.

E2.5 Power factor

A power factor of unity is assumed for heating events.

E.3 Factors for water heating demand – layer 3

E3.1 Scale

A water heater rating is selected from a choice of 1- 3 kW ratings. Larger semi or detached homes are assigned a rating of 3 kW. Average sized homes (around 88m^2 floor area) are assigned a rating of 2 kW. Smaller flats and terrace homes are assigned a rating of 1 kW. Events are assumed to have a constant demand level throughout, at this rated power.

E3.2 Timing

If an event is triggered, the duration is calculated by dividing the assigned half-hourly demand for water heating by the rated power (multiplied by 30 to give the duration in minutes). The start time is selected at random, such that the event is completed within the current half-hour.

E3.3 Frequency

The model does not control the frequency of events. Only one event can occur per half-hour and the model estimates several events per day.

E3.4 Triggering

A typical water heating event is assumed to last 15 minutes. The demand required to use the water heater at the rated power for this period is compared to the assigned demand in each half-hour to provide a probability of an event. If a randomly generated number is less than this probability, then an event occurs.

E3.5 Power factor

A power factor of unity is assumed for water heating events.

E.4 Factors for cooking demand – layer 3

E4.1 Scale

E4.1.1 Hobs

The demand per ring is either set at 1, 2kW or zero. Four rings may be triggered to operate. Per ring, the demand occurs in a pattern, which depends on the random selection of settings between 1-10, and repeats every five minutes. The demand patterns are given in Table E-1.

Hob setting	Demand for a single hob element (in kW)				
	0-1 minutes	1-2 minutes	2-3 minutes	3-4 minutes	4-5 minutes
0	0	0	0	0	0
1	1	0	0	0	0
2	2	0	0	0	0
3	2	1	0	0	0
4	2	2	0	0	0
5	2	2	1	0	0
6	2	2	2	0	0
7	2	2	2	1	0
8	2	2	2	2	0
9	2	2	2	2	1
10	2	2	2	2	2

Table E-1: Demand patterns over a five minute period for different settings of a hob ring

(Based on [Newborough & Augood, 1999])

The ring that is in use within a given half hour is selected randomly using the probabilities given in Table E-2.

Ring	**Probability ring is in use (%)**
Ring 1	97.6
Ring 2	83.5
Ring 3	53.9
Ring 4	44.6

(Based on [Mansouri et al, 1996] using data for the proportion of the sample who did not use a ring on an average day)

Table E-2: Probability that a hob ring is in use in a given half-hour

Each ring event is treated as an independent demand.

E4.1.2 Ovens

The demand during the initial pre-heat phase is set at 2.5 kW, remaining constant throughout the selected period. The cooking phase has a demand of 2 kW, switching in and out with a pattern depending on the oven level selected (chosen from 1 to 5). The cycle time is 10 minutes and the number of minutes in the heating period is equal to the setting selected. For example, if the setting selected is 1, the cooker is on for 1 minute and off for 9 minutes. If the selected setting is 5, the cooker remains on for 5 minutes and off for 5 minutes.

E4.1.3 Microwaves

A continuous demand of 0.005 kW is assumed to occur, to represent a standby demand. A microwave cooking event is assumed to have a constant demand at either 0.220 kW or 1.300 kW, representing a cooking event or a defrost event. The selection of demand level is made on a random basis using a probability that 20% of events are defrosting and 80% are cooking (based on [Mansouri et al, 1996]).

E4.1.4 Kettles

A kettle event is assumed to have a constant level of demand. The rated demand for kettle events is selected on a linear random basis, between 2-3 kW.

E4.2 Timing

E4.2.1 Hobs

The hob duration is selected randomly using the distribution given in Table E-3.

Ring	Probability of event duration (%)					
	<15min	15-30 min	30-45 min	45-60 min	60-120 min	120 -135 min
1	20.1	43.6	20.9	9.3	3.6	2.5
2	35.6	40.0	16.8	2.9	2.4	2.3
3	53.9	30.6	8.7	2.2	2.8	1.8
4	66.9	17.7	7.8	2.2	3.1	2.3

(Based on Mansouri et al's study[Mansouri et al, 1996])

Table E-3: Probability of the duration of a hob ring event

Start time for an event, if triggered, occurs at any time in a given half-hour.

E4.2.2 Ovens

The pre-heat phase for the oven is set at 5 minutes for an oven setting of 1 and 20 minutes for the maximum setting of 5, with a linear variation in between (the setting is selected randomly). The timing of the cooking phase is selected randomly, using a normal distribution (mean = 35 minutes, standard deviation of 10 minutes). (based on Mansouri et al's study [Mansouri et al, 1996])

The start time, if an event is triggered, is selected at random to occur at any time during the current half-hour.

E4.2.3 Microwaves

The duration of a microwave event depends on whether it is a defrost or cooking requirement. The distribution used to select a random duration is given by Table E-4 (based on Mansouri et al's study [Mansouri et al, 1996]).

Function	**Probability of event duration (%)**			
	<5min	5-10 min	10-20 min	20-30 min
Defrost	73	21	5	1
Cooking	51	29	14	6

Table E-4: Probability of the duration of a microwave event

The start time is selected randomly to occur at any time during the half-hour.

E4.2.4 Kettles

A kettle event can last between 2-5 minutes and the duration is selected randomly with a uniform distribution. The event may begin at any time within the half-hour.

E4.3 Frequency

The probability used for triggering a hob or oven event is adjusted to give typical daily frequency of use patterns. The frequency adjustment factor is used to scale the probability (Table E-5, trends based on MTP data for annual frequency of use of hobs and ovens [DEFRA, 2001]).

Appliance	Frequency adjustment factor				
	1970	1980	1990	2010	2020
Hob	1.34	1.02	0.92	0.92	0.92
Oven	2.77	1.32	1.05	0.83	0.67

Table E-5: Frequency adjustment factors used to ensure correct frequency of use

For ovens, a maximum of two events only are allowed per day. There is no additional control over the frequency of microwave and kettle events in the model.

E4.4 Triggering

E4.4.1 Hobs and ovens

The ratio of the assigned half-hourly demand to an average cooking event (Table E-6), adjusted by the frequency factor, is used as a probability that an event is triggered.

Appliance	Average event demand (kW, half-hourly averaged)
Hob	1.5
Oven	1.5

Table E-6: Average event demand per half-hour used to estimate probability value for triggering hob and oven events

E4.4.2 Kettles and microwaves

There is no explicit control over the frequency of use of kettles within the model. The ratio of the assigned half-hourly demand to the averaged demand required for the event (given by the rated power multiplied by the duration in minutes and divided by 30) is used for the probability that an event will occur. This ratio is adjusted by a scaling factor for microwaves (0.12 for defrost events and 0.87 for cooking events) used to ensure that the model estimates a typical average daily use pattern (of 5.5 minutes and 7 minutes per day respectively, based on [Mansouri et al, 1996]).

E4.5 Power factor

A power factor of unity is assumed for all cooking events.

E.5 Factors for wet appliance demand – layer 3

E5.1 Scale

E5.1.1 Washing machines

The demand fluctuates during the washing event and the pattern and duration depend on the random selection from three wash cycles (40°,60° and 90° cycles). The relative proportion and hence probability for each wash temperature follows trends provided by the MTP ([DEFRA,2001], Table E-7)

Year	Distribution of temperature selection for wash cycles		
	40 deg wash	60 deg wash	90 deg wash
1970	30%	45%	25%
1990	58%	36%	6%
1998	64%	34%	3%
2000	66%	32%	2%
2005	68%	30%	2%
2010	68%	30%	2%
2015	68%	30%	2%
2020	68%	30%	2%

Table E-7: Trends in the distribution of temperatures used for washing events ([DEFRA,2001])

The demand level varies during the wash cycle as heating elements, pump motors, spin motors and controls switch in and out. This depends on the particular wash cycle selected (Table E-8).

Time(min)	40 deg wash - load (kW)	60 deg wash - load (kW)	90 deg wash – load (kW)
1	0.05	0.05	0.05
2	0.05	0.05	0.05
3	0.3	0.3	0.3
4	0.3	0.3	0.3
5	2	2	2
6	2	2	2
7	2.05	2.05	2.05
8	2.1	2.1	2.1
9	2.1	2	2
10	2	2.05	2.05
11	2.05	2.05	2.05
12	2	2	2
13	2.1	2.1	2.1
14	2.05	2.05	2.05
15	0.3	2	2
16	0.25	2.05	2.05
17	0.1	2	2
18	0.05	2.1	2.1
19	0.45	2	2
20	0.3	2.1	2.1
21	0.25	0.1	2
22	0.75	0.05	2.05
23	0.05	2	2.1
24	0.05	2.1	2.1
25	0.45	0.3	2
26	0.3	0.25	2.05
27	0.25	0.1	2.1
28	0.75	0.05	2
29	0.05	0.45	2.1
30	0.05	0.3	2.05
31	0.45	0.25	2.1
32	0.3	0.75	2
33	0.25	0.05	2.1
34	0.75	0.05	2.05
35	0.05	0.45	2.1
36	0.05	0.3	2
37	0.05	0.25	2
38	0.3	0.75	2.1
39	0.3	0.05	2.05
40	0.1	0.05	2.1
41	0.75	0.45	0.1
42	0.4	0.3	0.05
43	0.4	0.25	2
44	0.4	0.75	2.1
45	0.1	0.05	0.1
46	0.1	0.05	0.05
47	0.1	0.05	2
48	0.1	0.3	2.1

Table E-8: (Continued overleaf)

(continued)

Time(min)	40 deg wash - load (kW)	60 deg wash - load (kW)	90 deg wash – load (kW)
49		0.3	0.1
50		0.1	0.05
51		0.75	2
52		0.4	2.1
53		0.4	0.3
54		0.4	0.25
55		0.1	0.1
56		0.1	0.05
57		0.1	0.45
58		0.1	0.3
59			0.25
60			0.75
61			0.05
62			0.05
63			0.45
64			0.3
65			0.25
66			0.75
67			0.05
68			0.05
69			0.45
70			0.3
71			0.25
72			0.75
73			0.05
74			0.05
75			0.05
76			0.3
77			0.3
78			0.1
79			0.75
80			0.4
81			0.4
82			0.4
83			0.1
84			0.1
85			0.1
86			0.1

Table E-8: Demand level variations (on a 1-minute averaged basis) during the three wash cycles (based on [Newborough & Augood, 1999]). Note - the shaded cells of the table are assumed to be periods when the spin motor is operating.

E5.1.2 Tumble dryers

An assumed tumble dryer pattern of demand is based on observations of an Ariston washer dryer in tumble dry mode (Table E-9). The model assumes a continuous demand of 0.005 kW for controls and 1.75 kW for a heater and fan with intermittent demands of 0.8kW for a pump (running for 18 seconds after every 75 seconds) and

1.5 kW for a spin motor (repeatedly operating after 82 seconds for 11 seconds and again for 5 seconds after a 27 second gap).

Time(min)	Active load for drying event (kW)	Reactive load for drying event(kW)
1	1.901	0.048
2	2.340	0.144
3	2.441	0.192
4	2.323	0.156
5	2.016	0.084
6	2.340	0.144
7	2.441	0.192
8	2.441	0.192
9	2.300	0.144
10	1.941	0.048
11	2.441	0.192
12	2.441	0.192
13	2.415	0.18
14	2.225	0.108
15	2.041	0.096
16	2.441	0.192
17	2.415	0.18
18	2.340	0.144
19	2.326	0.156
20	2.041	0.096
21	2.415	0.18
22	2.340	0.144
23	2.440	0.192
24	2.326	0.156
25	2.016	0.084
26	2.300	0.144
27	2.440	0.192
28	2.440	0.192
29	2.300	0.144
30	1.940	0.048
31	2.440	0.192
32	2.440	0.192
33	2.415	0.18
34	2.225	0.108
35	2.041	0.096
36	2.441	0.192
37	2.415	0.18
38	2.340	0.144
39	2.326	0.156
40	2.041	0.096
41	2.415	0.18
42	2.340	0.144
43	2.441	0.192
44	2.326	0.156
45	2.016	0.084
46	2.340	0.144
47	2.441	0.192
48	2.441	0.192

Table E-9: (continued overleaf)

Continued		
Time(min)	**Active load for drying event (kW)**	**Reactive load for drying event(kW)**
49	2.300	0.144
50	2.941	0.048
51	2.441	0.192
52	2.441	0.192
53	2.415	0.18
54	2.225	0.108
55	2.041	0.096
56	2.441	0.192
57	2.415	0.18
58	2.340	0.144
59	2.326	0.156
60	2.041	0.096
61	2.415	0.18
62	2.340	0.144
63	2.441	0.192
64	2.326	0.156
65	2.016	0.084
66	2.340	0.144
67	2.441	0.192
68	2.441	0.192
69	2.300	0.144
70	1.941	0.048
71	2.441	0.192
72	2.441	0.192
73	2.415	0.18
74	2.225	0.108
75	2.041	0.096
76	2.441	0.192
77	2.415	0.18
78	2.340	0.144
79	2.326	0.156
80	2.041	0.096
81	2.415	0.18
82	2.340	0.144
83	2.441	0.192
84	2.326	0.156
85	2.016	0.084
86	2.340	0.144
87	2.441	0.192
88	2.441	0.192
89	2.300	0.144
90	1.941	0.048
91	2.441	0.192
92	2.441	0.192
93	2.415	0.18
94	2.225	0.108
95	2.041	0.096
96	2.441	0.192
97	2.415	0.18
98	2.340	0.144
99	2.326	0.156

Table E-9: (continued overleaf)

Continued		
Time(min)	**Time(min)**	**Time(min)**
100	2.041	0.096
101	2.415	0.18
102	2.340	0.144
103	2.441	0.192
104	2.326	0.156
105	2.016	0.084
106	2.340	0.144
107	2.441	0.192
108	2.441	0.192
109	2.300	0.144
110	1.941	0.048
111	2.441	0.192
112	2.441	0.192
113	2.415	0.18
114	2.225	0.108
115	2.041	0.096
116	2.441	0.192
117	2.415	0.18
118	2.340	0.144
119	2.326	0.156
120	2.041	0.096

Table E-9: Pattern of active and reactive demands used by the model during a drying event

E5.1.3 Dishwashers

Dishwasher cycles are selected randomly from a choice of four programmes – two at 55° and two at 65° (based on Newborough & Augood's study [Newborough & Augood, 1999]).

The selection of temperature is made randomly using trends identified by the MTP ([DEFRA, 2001], Table E-10).

Year	**Distribution of temperature selection for dishwasher cycles**	
	65 deg wash %	**55 deg wash %**
1990	68	32
1998	64	36
2000	63	37
2005	59	41
2010	55	45
2015	51	49
2020	50	50

Table E-10: Trends in the distribution of temperatures used for dishwasher events

An even chance of either programme A or B is assumed. Demand levels vary during the event depending on which cycle has been selected (Table E-11).

Time (min)	Demand level during dishwasher event (kW)			
	Programme A-65°	Programme A-55°	Programme B-65°	Programme B-55°
1	0.2	0.2	0.2	0.2
2	0.2	0.2	0.2	0.2
3	0.2	0.2	0.2	0.2
4	0.2	0.2	0.05	0.05
5	0.1	0.1	0	0
6	0	0	0.2	0.2
7	0	0	0.2	0.2
8	0.2	0.2	2.1	2.1
9	2.7	2.7	2.1	2.1
10	2.7	2.7	2.1	2.1
11	2.7	2.7	2.1	2.1
12	2.7	2.7	2.1	2.1
13	2.7	2.7	2.1	2.1
14	2.7	2.7	2.1	2.1
15	2.7	2.7	2.1	2.1
16	2.7	2.7	2.1	0.2
17	2.7	2.7	2.1	0.2
18	2.7	0.2	2.1	0.2
19	2.7	0.2	2.1	0.2
20	2.7	0.2	2.1	0.2
21	2.7	0.2	0.2	0.2
22	2.7	0.2	0.2	0.2
23	0.2	0.2	0.2	0.2
24	0.2	0.2	0.2	0.2
25	0.2	0.2	0.2	0.2
26	0.2	0.2	0.2	0.05
27	0.2	0.2	0.2	0.2
28	0.2	0.2	0.2	0.2
29	0.2	0.2	0.2	0.2
30	0.2	0.1	0.2	0.2
31	0.2	0	0.05	0
32	0.2	0	0.2	0.2
33	0.2	0	0.2	0.2
34	0.2	0.2	0.2	0.2
35	0.1	0.2	0.2	0.05
36	0	0.1	0	0
37	0	0.1	0.2	0.2
38	0	0	0.2	0.2
39	0.2	0.2	0.2	2.1
40	0.2	0.2	0.05	2.1
41	0.1	0.1	0	2.1
42	0.1	0.1	0.2	2.1
43	0	0	0.2	2.15
44	0.2	0.2	2.1	2.15
45	0.2	2.7	2.1	2.15
46	0.1	2.7	2.1	0.2
47	0.1	2.7	2.1	0.2
48	0	2.7	2.15	0.2

Table E-11: (continued overleaf)

Continued				
Time (min)	Demand level during dishwasher event (kW)			
	Programme A-65°		Programme A-65°	
49	0.2	2.7	2.15	0.2
50	2.7	2.7	2.15	0.2
51	2.7	2.7	2.15	0.2
52	2.7	2.7	2.15	0.2
53	2.7	2.7	2.15	0.05
54	2.7	2.7	2.15	0
55	2.7	0.2	0.2	0
56	2.7	0.2	0.2	2.1
57	2.7	0.2	0.2	2.1
58	2.7	0.2	0.2	0
59	2.7	0.2	0.2	0
60	2.7	0.1	0.2	2.1
61	2.7	0.1	0.2	2.1
62	2.7	0	0.05	0.05
63	2.7	0	0	0
64	0.2	0	0	0
65	0.2	0	2.1	0
66	0.2	0	2.1	0
67	0.2	0	0	0
68	0.2	0	0	0
69	0.1	0	2.1	0
70	0.1	0	2.1	0
71	0	0	0.05	0

Table E-11: Pattern of demands used by the model during four different dishwasher event cycles

E5.2 Timing

The start time of a washing appliance event is set to occur at any time during the current half-hour. The duration depends on the cycle selected and events may run on through subsequent half-hourly periods.

For tumble dryers, two duty cycles with the same pattern of demand but different durations may be selected at random. The assumed probabilities used are a 75% chance of a 120 minute event and a 25% chance of a 90 minute event.

E5.3 Frequency

Only one washing event per appliance is allowed at any one time. The triggering of an event is controlled by scaling the probability (Table E-12) which ensures that the model predicts a frequency of use that is realistic (based on Mansouri et al's study [Mansouri et al, 1996]).

Appliance	Scaling factor for triggering an event	Associated number of typical cycles/ week
Washing machine	0.61	4.3
Tumble dryer	1.00	2.5
Dishwasher	0.33	5.3

Table E-12: Scaling factors used to adjust the frequency of use estimated by the model

E5.4 Triggering

To trigger a washing appliance event, the model uses the assigned half-hourly demand, multiplied by the frequency scaling factor and divided by the demand required in the first half-hour of the selected cycle. This probability is compared to a linearly generated random number to determine whether or not an event is triggered.

E5.5 Power factor

A power factor of unity is assumed for washing and drying events, except if the spin motor is operating when a power factor of 0.9 is assumed (designated by the shading in Table E-8 for washing machines and shown in the last column in Table E-9, for tumble dryers), based on Newborough & Augood's study [Newborough & Augood, 1999].

A power factor of unity is assumed throughout a dishwasher event.

E.6 Factors for lighting demand – layer 3

E6.1 Scale

The rating for an 'average' light bulb is used to set the level of demand for all individual lighting events. This is calculated using the relative proportion of different types of bulbs in use and their rated power (based on MTP 1998 data [DEFRA, 2001], Table E-13).

Lighting type	Rated power (kW)	Percentage of total bulb ownership
GLS – 60W	0.060	40%
GLS – 100W	0.100	34%
Fluorescent strip	0.063	12%
GLS – 40W	0.040	10%
CFL (Low energy)	0.015	3%
Halogen	0.030	1%

Table E-13: Rated power and relative levels of ownership for different types of light bulbs, used to establish the rated power of an 'average' bulb.

Using this basis, the model assumes that all lighting events occur at a level of 0.073 kW.

When lighting events have been triggered and the event timing selected, the scale of the events is varied such that their total half-hourly averaged demand equals that assigned.

E6.2 Timing

The duration of a lighting event is selected at random using a distribution based on a limited study of lighting in a single home for one week (4-person, detached house, above average income, 1st – 8th April, 2003). There is an equal probability associated with the duration being in each range (Table E-14) and within each range, the duration is selected randomly, on a linear basis.

The start time of each lighting event may occur at any time during the current half-hour if triggered.

Distribution of lighting event duration (minutes) – ranges having equal probability								
1	2	3-4	5-8	9-16	17-27	28-49	50-91	92-259

Table E-14: Distribution used to select a lighting event duration (each range has an equal probability)

E6.3 Frequency

Several lighting events may occur at the same time. If the current half-hourly demand is higher than in the previous one, more lighting events are likely to begin.

E6.4 Triggering

The assigned half-hourly lighting demand is divided by the rated power of the 'average' light bulb. The integer part of this value is used to trigger lighting events. The remaining fraction is used as a probability that a further lighting event may occur.

E6.5 Power factor

A power factor of unity is assumed for all lighting events.

E.7 Factors for miscellaneous demand – layer 3

E7.1 Scale

The scale of a miscellaneous event depends on which appliance is selected. The rated power of the appliance is assumed to remain constant throughout the event. Appliances are selected in relation to their assumed contribution to the total miscellaneous energy demand per day (Table E-15). Appliances are selected at random until most or all of the half-hourly assigned demand has been consumed (the model allows up to twenty appliance and timing selections to be made at random to determine a mix of requirements that in total can match the assigned demand). If the demand falls below 0.005kW, it is assumed that a further standby event occurs at 0.005kW throughout the half-hourly period.

Appliance	Typical power rating (kW)	Assumed typical use pattern				Probability (col. 6 / total kWh/day)
		No. per house	Average use/day (hours)	Average use/ week (days)	Typical energy used (kWh /day)	
TV	0.09	2.44	6.5	7	1.427	0.374
PC	0.115	1	4.5	7	0.518	0.136
Colour monitor	0.1	1	3	7	0.300	0.079
Hi Fi	0.5	1	1.5	2	0.214	0.056
Iron	1.5	1	0.5	2	0.214	0.056
Toaster	1	1	0.16	7	0.160	0.042
Digital box	0.045	1	3	7	0.135	0.035
Shaver	0.5	1	0.25	7	0.125	0.033
Alarm/ security	0.005	1	24	7	0.120	0.031
Vacuum cleaner	0.8	1	1	1	0.114	0.030
Fan heater	0.7	1	1	1	0.100	0.026
Chargers	0.004	13	4	3	0.089	0.023
Coffee maker	1.2	1	0.25	2	0.086	0.022
Deep fat fryer	1.8	1	0.25	1	0.064	0.017
Hob extractor	0.144	1	0.5	5	0.051	0.013
VCR	0.07	1	3	1	0.030	0.008
Stereo (portable)	0.055	1	1.5	2	0.024	0.006
CD/DVD	0.05	1	1.5	2	0.021	0.006
Hair dryer	0.75	1	0.05	2	0.011	0.003
Food processor	0.4	1	0.1	1	0.006	0.001
Printer	0.02	1	0.5	3	0.004	0.001
				Total energy used	**3.814**	

Table E-15: Assumptions used regarding use patterns to determine the probability that an appliance is use for a miscellaneous event

E7.2 Timing

An event duration is randomly selected on a linear basis within a range that depends on the appliance (Table E-16). The start time is set to occur at any time within the current half-hour.

Appliance	Assumed range of event duration (minutes)
TV	15 - 240
PC	15 - 240
Colour monitor	15 - 240
Hi Fi	15 - 30
Iron	15 - 120
Toaster	5
Digital box	15 -240
Shaver	5 - 15
Alarm/ security	1440
Vacuum cleaner	5 - 30
Fan heater	15 - 240
Chargers	240 - 480
Coffee maker	15 - 120
Deep fat fryer	10 - 20
Hob extractor	15 - 120
VCR	15 - 120
Stereo (portable)	15 -30
CD/DVD	15 -120
Hair dryer	5 - 20
Food processor	5 - 15
Printer	5 - 15

Table E- 16: Assumed range of duration for miscellaneous events and typical usage in the current half-hour if an event is triggered

E7.3 Frequency

The model does not directly control the frequency that miscellaneous events occur. This varies with the assigned half-hourly demand and the rating and timing selected for the event.

E7.4 Triggering

Once an appliance is selected, with randomly defined timing, the demand in the current half-hour is used to trigger the event (based on the product of the rated power, from Table E-15 and the event duration). If there is sufficient assigned demand remaining, the event is triggered.

E7.5 Power factor

A power factor of unity is assumed for all miscellaneous demand events.

Appendix F

Values for factors used in the non-domestic model

For non-domestic consumers, the approach based on the trends of domestic model, layer 1. Full details of this proposed method are provided in Chapter 7. This appendix includes values derived for non-domestic consumers in a variety of different activity categories.

F-1 Categories of non-domestic consumer

These categories are based on those used in the NBDS [Steadman et al, 2000] plus additional categories, wherever relevant data have been found. The current version of the model covers the following categories:

Shops

Baker
Bank
Bookshop
Business services
Butcher
Catalogue store
Car showroom/motor factor
Clothes shop
Dept. store
Distribution warehouse/wholesalers
DIY store
Dry-cleaners
Electrical goods-rental
Electrical goods retail
Food - corner shop
Food- larger shop
Frozen food centre
Hairdresser or barber
Hire shop – general
Hypermarket
Laundrette
Newsagents/sweets/tobacco
Off-licence
Printers
Repair shop

Service shop – personal

Supermarket

Shoe shop

Unknown (assigned randomly from other categories, even distribution)

Offices

Cellular/naturally ventilated

Open plan/naturally ventilated

Mechanically ventilated/ air conditioned

Unknown (randomly assigned from other categories in ratio 60.4/25.9/13.6%)

Schools

State primary

State secondary

Special

Private primary/secondary

Unknown (randomly assigned, even distribution)

Hotels

Hotel

Motel

Guest House

Boarding house/hostel

Residential care home

Unknown (randomly assigned, even distribution)

Places of worship

Church

Industrial

Engineering

This list of categories may be extended in line with the NBDS categories, using additional data and the generalised method (described in Chapter 7).

F-2 Shops

F-2.1 Shops - Floor Areas

Shop category	Floor area (m²) distribution				
	Minimum	1st quartile	mean	3rd quartile	Maximum
Baker	28	99	148	360	1586
Bank	66	172	299	358	3091
Bookshop	28	99	148	360	1586
Business services	79	146	200	306	347
Butcher	52	58	106	185	271
Catalogue store	28	99	148	360	1586
Car showroom/motor factor	298	499	849	1475	2247
Clothes shop	28	99	148	360	1586
Dept. store	1247	1938	2732	3809	4557
Distribution warehouse/wholesalers	79	138	330	814	38272
DIY store	28	99	148	360	1586
Dry-cleaners	81	99	193	195	1884
Electrical goods – rental	28	99	148	360	1586
Electrical goods – retail	28	99	148	360	1586
Food – corner shop	22	41	76	167	303
Food –larger shop	28	99	148	360	1586
Frozen food centre	28	99	148	360	1586
Hairdressers/barber	30	66	103	138	360
Hire shop	28	99	148	360	1586
Hypermarket	230	287	1629	6459	12216
Laundrette	81	99	193	195	1884
Newsagents/sweets/tobacco	34	66	98	121	587
Off-licence	34	66	98	121	587
Printers	111	121	357	1077	3531
Repair shop	125	189	312	536	813
Service shop – personal	37	120	129	189	252
Shoe shop	28	99	148	360	1586
Supermarket	196	1275	1534	3250	4995

Based on [Bruhns et al, 2000]

Table F-1: Values used for estimating floor areas for retail consumers

When no specific information is available regarding the floor area, the model uses a random value, selected in line with the distribution above.

F-2.2 Shops - Specific annual energy consumption

Shop category	Specific annual consumption (kWh/m²/year)				
	Minimum	1st quartile	mean	3rd quartile	Maximum
*Baker[1]	34	105	181	217	772
Bank					
all electric	20	122	195	275	780
mixed fuels	5	71	101	131	460
Bookshop	70	210	255	295	430
*Business services	45	152	195	248	291
Butcher	220	475	577	680	1300
Catalogue store					
all electric	50	100	133	150	240
mixed fuels	35	83	101	120	250
*Car showroom/motor factor	79	201	259	349	378
Clothes shop					
all electric	60	287	324	395	1030
mixed fuels	175	234	270	285	700
Dept. store					
all electric	75	209	259	309	550
mixed fuels	90	237	294	350	830
*Distribution warehouse/wholesalers	1	42	118	157	385
DIY store	80	127	160	195	280
Dry-cleaners	359	783	1076	1467	1641
*Electrical goods – rental[1]	34	105	181	217	772
Electrical goods – retail	60	172	230	260	590
Food – corner shop	18	83	165	230	453
Food – larger shop	720	1030	1180	1280	1600
Frozen food centre	360	857	1029	1230	1960
*Hairdressers/barber	158	244	339	411	583
*Hire shop[1]	34	105	181	217	772
*Hypermarket	112	141	349	589	758
Laundrette	359	783	1076	1467	1641
*Newsagents/sweets/ tobacco	59	127	199	276	352
Off-licence	475	475	562	562	562
*Printers	76	155	200	205	431
*Repair shop	28	54	85	99	163
*Service shop – personal[2]	45	152	195	248	291
Shoe shop	197	197	279	279	279
Supermarket					
all electric	720	1030	1180	1280	1600
mixed fuels	600	910	1020	1180	1580

[1]Data based on values for a general store
[2] Data based on business services shop
* Data from [Pout, 2000], other data from [Jones et al, 1999b]

Table F-2: Values used for estimating specific annual energy consumption for retail consumers

When no specific data are available, the model estimates the specific energy consumption using the distributions of Table F-2.

F-2.3 Shops - Proportion of energy supplied by electricity

The data taken from [Jones et al, 1999b], presented in Table F-2, already provides estimates of the electricity consumption. The remaining data, from [Pout,2000] are the annual energy consumption values and must be apportioned to provide the contribution of supply from electricity, using the values in Table F-3:

Shop category	Proportion of annual fuel consumption provided by electricity
Baker	0.842
Business services	0.440
Car showroom/motor factor	0.278
Distribution warehouse/wholesalers	0.382
Dry cleaners	0.092
Electrical goods – rental	0.842
Hairdressers/barber	0.501
Hire shop	0.842
Hypermarket	0.925
Newsagents/sweets/tobacco	0.888
Printers	0.659
Repair shop	0.423
*Service shop – personal[2]	0.440

Data based on [Pout, 2000]

Table F-3: Values used for estimating proportion of annual energy demand provided by electricity for retail consumers

F-2.4 Shops - End-use proportions

Shop category	Proportion of annual electricity consumption – by end-use					
	Heating	Lighting	Water heating	Cooking	Cooling	Miscellaneous
Baker	0.29	0.09	0.02	0.49	0.02	0.09
Bank	0.19	0.13	0.04	0.33	0.04	0.27
Bookshop	0.29	0.09	0.02	0.49	0.02	0.09
Business services	0.38	0.01	0.08	0.35	0.04	0.14
Butcher	0.02	0.05	0.07	0.16	0.62	0.08
Catalogue store	0.29	0.09	0.02	0.49	0.02	0.09
Car showroom/motor factor	0.07	0.01	0.03	0.56	0.06	0.26
Clothes shop	0.29	0.09	0.02	0.49	0.02	0.09
Dept. store	0.10	0.11	0.01	0.55	0.04	0.18
Distribution warehouse/wholesalers	0.21	0.07	0.01	0.56	0.02	0.13
DIY store	0.29	0.09	0.02	0.49	0.02	0.09
Dry-cleaners	0.01	0.01	0.01	0.18	0.01	0.77
Electrical goods – rental	0.29	0.09	0.02	0.49	0.02	0.09
Electrical goods – retail	0.29	0.09	0.02	0.49	0.02	0.09
Food – corner shop	0.07	0.01	0.07	0.31	0.47	0.07
Food –larger shop	0.07	0.01	0.07	0.31	0.47	0.07
Frozen food centre	0.16	0.52	0.02	0.19	0.04	0.07
Hairdressers/barber	0.28	0.00	0.11	0.22	0.03	0.36
Hire shop	0.29	0.09	0.02	0.49	0.02	0.09
Hypermarket	0.02	0.71	0.00	0.18	0.00	0.08
Laundrette	0.01	0.01	0.01	0.18	0.01	0.77
Newsagents/sweets/tobacco	0.27	0.03	0.03	0.40	0.18	0.09
Off-licence	0.27	0.03	0.03	0.40	0.18	0.09
Printers	0.05	0.18	0.00	0.25	0.04	0.48
Repair shop	0.21	0.01	0.02	0.45	0.04	0.26
Service shop – personal	0.39	0.01	0.02	0.41	0.02	0.15
Shoe shop	0.29	0.09	0.02	0.49	0.02	0.09
Supermarket	0.04	0.04	0.01	0.30	0.46	0.16

Based on [Elsayed et al, 2002]

Table F-4: Values used for estimating proportion of electrical demand by end-use for retail consumers

F-2.5 Shops – Daily Profiles

A daily profile is assumed, based on [Norén,1997], using the averaged half-hourly daily profile, divided by the annual mean demand.

Half hourly reference	Relative demand level for all office consumers (half-hourly averaged) compared to annual mean demand			
	Weekdays	Saturdays	Sundays	Unoccupied days (public holidays)
1	0.6670	0.6280	0.6280	0.6280
2	0.6600	0.6465	0.6465	0.6465
3	0.6540	0.6650	0.6650	0.6650
4	0.6500	0.6590	0.6590	0.6590
5	0.6450	0.6530	0.6530	0.6530
6	0.6400	0.6475	0.6475	0.6475
7	0.6340	0.6420	0.6420	0.6420
8	0.6330	0.6345	0.6345	0.6345
9	0.6320	0.6270	0.6270	0.6270
10	0.6490	0.6360	0.6360	0.6360
11	0.6670	0.6450	0.6450	0.6450
12	0.7380	0.7045	0.7045	0.6600
13	0.8090	0.7640	0.7640	0.6750
14	0.9735	0.9505	0.9505	0.6925
15	1.1380	1.1370	1.1370	0.7100
16	1.2275	1.2190	1.2190	0.7150
17	1.3170	1.3010	1.3010	0.7200
18	1.3525	1.3395	1.3395	0.7250
19	1.3880	1.3780	1.3780	0.7300
20	1.3970	1.3830	1.3830	0.7350
21	1.4070	1.3880	1.3880	0.7400
22	1.4120	1.3920	1.3920	0.7450
23	1.4170	1.3960	1.3960	0.7500
24	1.4210	1.3945	1.3945	0.7490
25	1.4250	1.3930	1.3930	0.7480
26	1.4160	1.3835	1.3815	0.7470
27	1.4070	1.3740	1.3700	0.7460
28	1.4120	1.3720	1.3435	0.7450
29	1.4160	1.3700	1.3170	0.7440
30	1.4140	1.3435	1.2470	0.7430

Table F-5: (Continued overleaf)

Continued				
Half hourly reference	Relative demand level for all office consumers (half-hourly averaged) compared to annual mean demand			
	Weekdays	Saturdays	Sundays	Unoccupied days (public holidays)
31	1.4130	1.3170	1.1770	0.7420
32	1.4080	1.2470	1.0680	0.7410
33	1.4030	1.1770	0.9590	0.7400
34	1.3940	1.0680	0.8600	0.7390
35	1.3850	0.9590	0.7610	0.7380
36	1.3670	0.8600	0.7475	0.7370
37	1.3490	0.7610	0.7400	0.7360
38	1.2970	0.7475	0.7370	0.7350
40	1.2450	0.7340	0.7340	0.7340
41	1.1375	0.7340	0.7340	0.7340
42	1.0300	0.7340	0.7340	0.7340
43	0.9255	0.7270	0.7270	0.7270
44	0.8210	0.7200	0.7200	0.7200
45	0.7660	0.6925	0.6925	0.6925
46	0.7110	0.6650	0.6650	0.6650
47	0.6975	0.6570	0.6570	0.6570
48	0.6840	0.6490	0.6490	0.6490

Table F-5: Values used for estimating daily profiles for shop based consumers

F-3 Offices

F-3.1 Offices - Floor Areas

If the office category is unknown, this is assigned randomly on the basis:

Cellular/naturally ventilated:	60.4%
Open plan/naturally ventilated:	13.6%
Mechanically ventilated:	25.9%

Using the office categories, unless a specific floor area is provided, the model assumes the following distributions for random assignment:

Cellular/naturally ventilated offices

37-500 m^2:	82%
500-1000 m^2:	10%
1000-5300 m^2:	8%

Open plan/naturally ventilated offices:

178-500 m^2:	46%
1500-2000 m^2:	8%
3500-4000 m^2:	8%
4000-4500 m^2:	18%
7500-8000 m^2:	20%

Mechanically ventilated/air conditioned offices:

266-500 m^2:	5%
500-1000 m^2:	10%
1000-1500 m^2:	10%
2500-3000 m^2:	10%
3000-3500 m^2:	5%
3500-4000 m^2:	18%
4000-4500 m^2:	5%
4500-5000 m^2:	5%
5500-6000 m^2:	5%
6000-6500 m^2:	5%
6500-7000 m^2:	18%
8500-9000 m^2:	4%

For the smallest category of cellular/naturally ventilated offices, a Gaussian distribution is assumed (mean value 254 m^2 and standard deviation 32.25 m^2, lower limit of 37 m^2 assumed) since the group is very large. Otherwise, the assignment is based on a linear distribution between the class limits. Values are based on [Elsayed et al, 2002]

F-3.2 Offices - Specific annual energy consumption

For random assignment of specific annual energy consumption in offices, a Gaussian distribution is used, with upper and lower boundaries (Table F-6).

Office category	Specific annual energy consumption (kWh/ m^2/year)			
	Mean	Standard deviation	Lower limit	Upper limit
Cellular/nat. vent.	184	75	38	496
Open plan/nat. vent.	240	90	104	422
Mech. Vent./Air con.	284	124	134	535

Based on [Elsayed et al, 2002]

Table F-6: Values used for estimating specific annual energy consumption for office based consumers

F-3.3 Offices - Proportion of energy supplied by electricity

The following proportions are used for offices to define the annual electricity consumption as a proportion of the total energy used:

Cellular/naturally ventilated: 0.268

Open plan/naturally ventilated: 0.378

Mechanically ventilated: 0.712

Based on [Elsayed et al, 2002]

F-3.4 Offices - End-use proportions

Annual electricity consumption is apportioned by office category (Table F-7).

Office category	Proportion of annual electricity consumption – by end-use					
	Lighting	Lighting	Lighting	Lighting	Lighting	Lighting
Cellular/nat. vent.	0.243	0.427	0.019	0.037	0.012	0.262
Open plan/nat. vent.	0.048	0.381	0.056	0.172	0.003	0.340
Mech. Vent./Air con.	0.128	0.200	0.014	0.038	0.337	0.283

Based on [Elsayed et al, 2002]

Table F-7: Values used for estimating proportion of electrical demand by end-use for office based consumers

F-3.5 Offices – daily profiles

Half-hour ref.	Relative demand level for all office consumers (half-hourly averaged) compared to annual mean demand	
	Weekdays	Unoccupied days (weekends & public holidays)
1	0.774	0.733
2	0.774	0.733
3	0.774	0.733
4	0.768	0.728
5	0.763	0.723
6	0.759	0.719
7	0.755	0.715
8	0.754	0.709
9	0.754	0.703
10	0.764	0.697
11	0.775	0.691
12	0.816	0.687
13	0.858	0.684
14	0.994	0.698
15	1.131	0.712
16	1.247	0.724
17	1.363	0.736
18	1.421	0.740
19	1.479	0.744
20	1.510	0.751
21	1.542	0.758
22	1.552	0.759
23	1.563	0.761
24	1.563	0.763
25	1.564	0.765
26	1.548	0.766
27	1.533	0.768
28	1.511	0.766
29	1.490	0.765
30	1.453	0.764
31	1.416	0.764
32	1.352	0.761
33	1.288	0.758
34	1.220	0.750
35	1.152	0.743
36	1.064	0.734
37	0.977	0.726
38	0.942	0.726
40	0.908	0.727
41	0.888	0.726
42	0.869	0.725
43	0.851	0.727
44	0.834	0.730
45	0.825	0.738
46	0.816	0.747
47	0.804	0.744
48	0.793	0.742

Based on [Norén, 1997]

Table F-8: Values used for estimating daily profiles for office based consumers

F-4 Schools

F-4.1 Schools - Floor Areas

Random selection of floor areas is made using a Gaussian distribution, using upper and lower boundaries (Table F-9).

School category	Floor area (m^2)	
	Mean	Standard deviation
State primary	1518	190
State secondary	7425	928
Special school	664	83
Private school	2400	300
Unknown type	2386	298

Based on [Bruhns et al, 2000]

Table F-9: Values used for random assignment of floor areas for schools

Lower limit set at $500m^2$

Upper limit at 18500 m^2 (based on data for Nottingham schools)

F-4.2 Schools - Specific annual energy consumption

A random assignment of the specific annual energy consumption is made on the basis of a Gaussian distribution, using a mean value of 224 kWh/m^2/annum and a standard deviation of 106 [Mortimer et al, 2000].

F-4.3 Schools - Proportion of energy supplied by electricity

34% of the annual energy consumption is assumed to be provided by electricity in all types of schools [Pout, 2000].

F-4.4 Schools - End-use proportions

The following proportions are used to provide annual assignments of electricity consumption by end-use:

Heating	0.14
Lighting	0.43
Water heating	0.05
Cooking	0.14
Cooling	0.05
Miscellaneous	0.12

F-4.5 Schools – daily profiles

Half-hour ref.	Relative demand level for all schools (half-hourly averaged) compared to annual mean demand	
	Weekdays	Unoccupied days (weekends/ public/ school holidays)
1	0.550	0.500
2	0.550	0.500
3	0.550	0.500
4	0.550	0.500
5	0.560	0.500
6	0.570	0.500
7	0.580	0.500
8	0.600	0.500
9	0.630	0.500
10	0.650	0.500
11	0.670	0.510
12	0.700	0.520
13	0.750	0.530
14	0.800	0.540
15	0.950	0.550
16	1.200	0.540
17	1.400	0.530
18	1.500	0.520
19	1.700	0.530
20	1.900	0.540
21	2.000	0.550
22	2.250	0.600
23	2.270	0.600
24	2.290	0.600
25	2.290	0.600
26	2.270	0.600
27	2.250	0.600
28	2.200	0.600
29	2.100	0.600
30	1.900	0.600
31	1.800	0.600
32	1.750	0.600
33	1.650	0.600
34	1.450	0.600
35	1.250	0.600
36	1.100	0.550
37	1.080	0.550
38	1.060	0.550
40	1.040	0.550
41	1.020	0.550
42	1.010	0.540
43	1.000	0.530
44	0.900	0.520
45	0.800	0.510
46	0.750	0.500
47	0.700	0.500
48	0.650	0.500

Table F-10: Values used for estimating daily profiles for schools

F-5 Hotels

F-5.1 Hotels - Floor Areas

For the purposes of the model, hotels and motels are assumed to have floor areas greater than 1000 m^2 whilst guest houses, hostels, boarding houses and care homes are less than 1000m^2. Random assignment is made using the following distributions, using a linear random selection within each class.

Hotels and motels:

1000-1500 m^2	0.22
1500-2000	0.22
2000-3000	0.22
5500-7000	0.22
7500-8500	0.12

Guest & boarding houses, hostels, care homes:

152-500 m^2	0.27
500-1000	0.73

Based on [Elsayed et al, 2002]

F-5.2 Hotels - Specific annual energy consumption

Specific energy consumption values are selected from the distribution below, using a linear distribution within each class.

121-139 kWh/ m^2/annum	0.10
139-278	0.25
278-417	0.34
417-556	0.10
556-834	0.08
834-973	0.09
1112-1223	0.04

Based on [Elsayed et al, 2002]

F-5.3 Hotels - Proportion of energy supplied by electricity

22% of the annual energy consumption in hotels is assumed to be provided by electricity (based on [Elsayed et al, 2002]).

F-5.4 Hotels - End-use proportions

The following proportions are used to provide annual assignments of electricity consumption by end-use in all categories of hotel:

Heating	0.09
Lighting	0.40
Water heating	0.03
Cooking	0.27
Cooling	0.06
Miscellaneous	0.15

If no specific information is available, space and water heating are assigned using a proportion of 4%. All hotel categories are assumed to use electricity for cooking (although most of the cooking demand is provided by gas).
Based on [Elsayed et al, 2002]

F-5.5 Hotels – daily profiles

Two separate daily profiles, a general profile and a specific version for care homes (Tables F-11 and F-12). These are based on Norén [Norén, 1997].

Hotels, guest houses, boarding houses, hostels

Half-hour ref.	Relative demand level for hotels, except for care homes (half-hourly averaged) compared to annual mean demand	
	Weekdays	Weekends & public holidays
1	0.794	0.749
2	0.744	0.734
3	0.695	0.719
4	0.676	0.696
5	0.657	0.674
6	0.647	0.660
7	0.638	0.646
8	0.633	0.640
9	0.628	0.634
10	0.660	0.641
11	0.693	0.649
12	0.759	0.702
13	0.826	0.755
14	0.914	0.802
15	1.002	0.850
16	1.074	0.881
17	1.146	0.913
18	1.175	0.941
19	1.204	0.969
20	1.214	0.979
21	1.225	0.989
22	1.231	0.994
23	1.238	1.000
24	1.236	0.992
25	1.235	0.985
26	1.226	0.979
27	1.218	0.973
28	1.201	0.972
29	1.184	0.972
30	1.174	0.981
31	1.165	0.990
32	1.156	0.989
33	1.147	0.988
34	1.149	0.990
35	1.152	0.993
36	1.151	0.997
37	1.151	1.001
38	1.153	1.000
40	1.155	1.000
41	1.154	0.998
42	1.154	0.996
43	1.147	0.986
44	1.140	0.977
45	1.104	0.947
46	1.068	0.917
47	0.997	0.874
48	0.926	0.831

Table F-11: Values used for estimating daily profiles for hotels, except care homes

Residential care homes

Half-hour ref.	Relative demand level for residential care homes (half-hourly averaged) compared to annual mean demand	
	Weekdays	Weekends & public holidays
1	0.690	0.681
2	0.687	0.680
3	0.684	0.679
4	0.684	0.680
5	0.684	0.681
6	0.682	0.679
7	0.681	0.677
8	0.675	0.669
9	0.670	0.662
10	0.690	0.668
11	0.710	0.674
12	0.788	0.717
13	0.867	0.760
14	1.002	0.845
15	1.137	0.930
16	1.231	0.959
17	1.325	0.989
18	1.373	1.012
19	1.421	1.035
20	1.470	1.077
21	1.519	1.120
22	1.495	1.094
23	1.472	1.069
24	1.433	1.042
25	1.394	1.016
26	1.391	1.023
27	1.388	1.031
28	1.372	1.023
29	1.357	1.016
30	1.326	1.000
31	1.296	0.985
32	1.239	0.970
33	1.182	0.956
34	1.130	0.949
35	1.078	0.943
36	1.040	0.922
37	1.003	0.902
38	0.977	0.891
40	0.952	0.880
41	0.914	0.846
42	0.876	0.813
43	0.840	0.788
44	0.805	0.763
45	0.780	0.747
46	0.756	0.732
47	0.741	0.725
48	0.727	0.718

Table F-12: Values used for estimating daily profiles for residential care homes

F-6 Places of worship (church)

F-6.1 Places of Worship - Floor Areas

Floor areas for churches are assigned randomly using a distribution based on the NBDS data.

166-500 m^2	0.45
500-1000	0.22
1000-1026	0.33

Based on [Elsayed et al, 2002]

F-6.2 Places of worship - Specific annual energy consumption

Random assignment of the specific annual energy consumption is made using a Gaussian distribution with mean of 129 kWh/m^2/annum and standard distribution of 85 [Elsayed et al, 2002]

F-6.3 Places of worship - Proportion of energy supplied by electricity

14.7% of the annual energy consumption is assumed to be provided by electricity [Elsayed et al, 2002]

F-6.4 Places of worship - End-use proportions

The following proportions are used to provide annual assignments of electricity consumption by end-use in churches:

Heating	0.26
Lighting	0.35
Water heating	0.07
Cooking	0.14
Cooling	0.00
Miscellaneous	0.18

There is a 4% chance assumed for space heating by electricity, 31% chance of water heating and an 84% chance of electricity use for cooking in churches.

Based on [Elsayed et al, 2002]

F-6.5 Places of worship – daily profiles

The daily profile for churches (Table F-13) is based on an assumed pattern of activity for weekdays, Saturdays and Sundays.

Half hour ref.	**Relative demand level for churches (half-hourly averaged) compared to annual mean demand**		
	Weekdays	Saturdays	**Sundays**
1	0.500	0.100	0.100
2	0.500	0.100	0.100
3	0.500	0.100	0.100
4	0.500	0.100	0.100
5	0.500	0.200	0.200
6	0.500	0.200	0.200
7	0.500	0.200	0.200
8	0.500	0.200	0.200
9	0.500	0.200	0.200
10	0.500	0.200	0.200
11	0.510	0.300	0.300
12	0.520	0.400	0.400
13	0.530	0.500	0.500
14	0.540	0.750	0.750
15	0.550	0.800	0.800
16	0.540	1.000	1.000
17	0.530	1.100	1.100
18	0.520	1.200	1.200
19	0.530	1.100	1.100
20	0.540	1.050	1.050
21	0.550	1.000	1.000
22	0.600	1.000	1.000
23	0.600	1.000	1.000
24	0.600	1.000	1.000
25	0.600	1.000	1.000
26	0.600	1.000	1.000
27	0.600	1.000	0.800
28	0.600	1.000	0.700
29	0.600	1.000	0.600
30	0.600	1.000	0.500
31	0.600	1.000	0.500
32	0.600	1.000	0.500
33	0.600	1.000	0.750
34	0.600	1.000	0.800
35	0.600	1.000	1.000
36	0.550	1.100	1.100
37	0.550	1.200	1.200
38	0.550	1.100	1.100
40	0.550	1.050	1.050
41	0.550	1.000	1.000
42	0.540	1.000	1.000
43	0.530	0.500	0.500
44	0.520	0.200	0.200
45	0.510	0.200	0.200
46	0.500	0.100	0.100
47	0.500	0.100	0.100
48	0.500	0.100	0.100

Table F-13: Values used for estimating daily profiles for churches (assumed profiles)

F-7 Industrial (engineering)

F-7.1 Industrial - Floor Areas

Floor areas are assigned randomly using linear probability within specific classes.

25-500 m^2	0.60
500-1000	0.22
1000-5597	0.18

Based on manufacturing businesses, assessed within the NBDS [Elsayed et al, 2002]

F-7.2 Industrial - Specific annual energy consumption

Specific energy consumption values are selected from the distribution below, using a linear distribution within each class.

25 - 139 kWh/ m^2/annum	0.35
139-278	0.34
278-417	0.16
417-556	0.06
556-695	0.03
695-834	0.03
834-973	0.03

Based on [Elsayed et al, 2002]

F-7.3 Industrial - Proportion of energy supplied by electricity

56.5% of the annual energy consumption is assumed to be provided by electricity for industrial consumers [Elsayed et al, 2002]

F-7.4 Industrial - End-use proportions

The following proportions are used to provide annual assignments of electricity consumption by end-use in manufacturing companies (including process energy use within the miscellaneous category):

Heating	0.02
Lighting	0.11
Water heating	0.00
Cooking	0.02
Cooling	0.00

Miscellaneous 0.85

There is a 4% probability of electricity being used for space heating, 6% for water heating and 82% for cooking.
Based on [Elsayed et al, 2002]

F-7.5 Industrial – daily profiles

The weekday daily profile is based on the LRG assessment of the half-hourly demands of engineering consumers (based on averaged winter weekdays, Figure 2-7). The unoccupied profile is based on assumed activity patterns (Table F-14).

Half-hour ref.	Relative demand level for engineering consumers (half-hourly averaged) compared to profile mean value	
	Weekdays	Unoccupied days (weekends & public holidays)
1	0.220	0.220
2	0.220	0.220
3	0.220	0.220
4	0.220	0.220
5	0.230	0.230
6	0.230	0.230
7	0.230	0.230
8	0.230	0.230
9	0.250	0.250
10	0.250	0.250
11	0.280	0.280
12	0.290	0.290
13	0.470	0.290
14	0.550	0.290
15	0.830	0.290
16	1.500	0.290
17	2.050	0.290
18	2.220	0.290
19	2.240	0.290
20	2.240	0.290
21	2.200	0.290
22	2.200	0.290
23	2.200	0.290
24	2.200	0.290
25	2.160	0.290
26	2.020	0.290
27	1.940	0.290
28	1.990	0.290
29	1.990	0.290

Table F-14: (Continued overleaf)

Continued		
Half-hour ref.	Relative demand level for engineering consumers (half-hourly averaged) compared to profile mean value	
	Weekdays	Unoccupied days (weekends & public holidays)
30	1.970	0.290
31	1.940	0.290
32	1.910	0.290
33	1.550	0.290
34	1.330	0.290
35	1.000	0.290
36	0.780	0.290
37	0.550	0.290
38	0.440	0.290
40	0.330	0.290
41	0.280	0.280
42	0.270	0.270
43	0.260	0.260
44	0.250	0.250
45	0.250	0.250
46	0.250	0.250
47	0.250	0.250
48	0.250	0.250

Table F-14: Values used for estimating daily profiles for engineering industrial consumers (based on LRG winter weekday averaged profile and assumed profile for unoccupied days)

Appendix

G

Solar thermal and Photovoltaic Models

The models that have been described in chapters 3 to 7 aim to provide realistic electrical demands on a 1-minute time scale and for individual consumers. They are designed to offer a practical representation of the diversity that exists between consumers within an urban area. Whilst not intended to be a core part of this research, models for solar yield operating in a similar vein to the load models were developed. This appendix gives a brief description of such models and endeavours to show how the predicted output from solar devices can reduce or eliminate demands calculated by the load models.

The Solar City project, with which the load models are associated, is concerned with the effects of solar technologies such as photovoltaic and solar thermal panels, since these are the most appropriate renewable energy collectors in urban areas. In practice, it is most likely that solar panels will be installed on sloping roof surfaces and the following sections describe simplified methods for estimating the solar energy falling on a tilted surface and the associated output expected from PV and solar water heating panels.

G.1 Available solar energy

G.1.1 Global horizontal irradiance

The irradiance falling on a horizontal surface (the global irradiance) is considered to be comprised of two components – the direct (or beam irradiance) and the diffuse irradiance. These components depend on the distance of the solar panel from and relative position to the sun as well as cloud cover and over-shading.

Frequently measured on a 1-minute basis, the direct and diffuse components at a given location are usually provided as hourly, or half-hourly, averages. Such data are widely available, generally on a commercial basis (for example [Meteonorm, 2004]) although some data are provided freely from European projects such as S@tel-Light [S@tel-Light, 2004] and SoDa [SoDa, 2004]. Probability distribution functions derived by Tovar et al [Tovar et al, 2001] are used to re-synthesise the 1-minute irradiation on a random basis from the hourly values, using the clearness index. This index is the ratio of the solar global irradiance falling on a horizontal surface, compared to that received at the top of the atmosphere (Equation G-1).

$$k_{TH} = E_{eg} / E_{ET} \qquad \textbf{[G-1]}$$

where:

k_{TH} is the hourly averaged clearness index

E_{eg} is the hourly global irradiance on a horizontal surface (W/m^2)

E_{ET} is the hourly extra-terrestrial irradiance (W/m^2)

For the purposes of this research, global irradiance values provided by the S@tel-Light project [S@tel-Light, 2004] were used, generated for Leicester (latitude 52° 37′ N, longitude 1° 7′ W and average altitude 77m above sea level). The hourly extra-terrestrial irradiance can be calculated from the angular displacement of the sun from the noon position, ω, the solar declination angle (angular position of the sun at noon with respect to the plane of the equator), δ, and the day number, N (Equations G-2 to G-4).

$$E_{ET} = G_0 x[1+0.033 \times \cos(360 \times N/N_y)] \times [\cos\varphi \times \cos\omega \cos\delta + \sin\varphi \times \sin\delta] \qquad \textbf{[G-2]}$$

where

G_0 is the solar constant (1367 W/m^2)

N is the Julian day number

N_y is the number of days in a given year

φ is the latitude (in degrees)

ω (in degrees) is given by:

$\omega = 15 \times (t - 2)$ **[G-3]**

where:

t is the time (based on a 24-hour clock) at the half-hour of the period of interest (this is modified at the start and end of the day if sunrise occurs after the half-hour or sunset before the half-hour. Under these circumstance the first and last hourly period are based on t being the time at the nearest hour).

δ (in degrees) is given by:

$\delta = 23.45 \times \sin(360 \times N/N_y)$ **[G-4]**

Using these calculated values for the clearness index, k_{TH}, the distributions of the 1-minute averaged clearness index, k_t, can be determined [Tovar et al, 2001]. The data used for the distributions was gathered over a three year period in south eastern Spain. Whilst clearness index distributions are generally site specific, Tovar et al's research relates the 1-minute indices to the hourly value and for the purposes of this research, it is assumed that these relationships are also valid for sites in the UK. The distributions of the clearness index at the 1-minute level are based on Boltzmann's statistics (Equation G-5).

$f(k_t|k_{TH}) = A \times \lambda \times e^{((kt-kto)\,\lambda)} / (1+e^{(kt-kto)\,\lambda})^2$ **[G-5]**

A and λ are constants for a given distribution and are calculated using polynomial relationships from the hourly values for the clearness index, k_{TH}. The distribution function is normalised by setting the area under the distribution curve to be unity (Figure G-1).

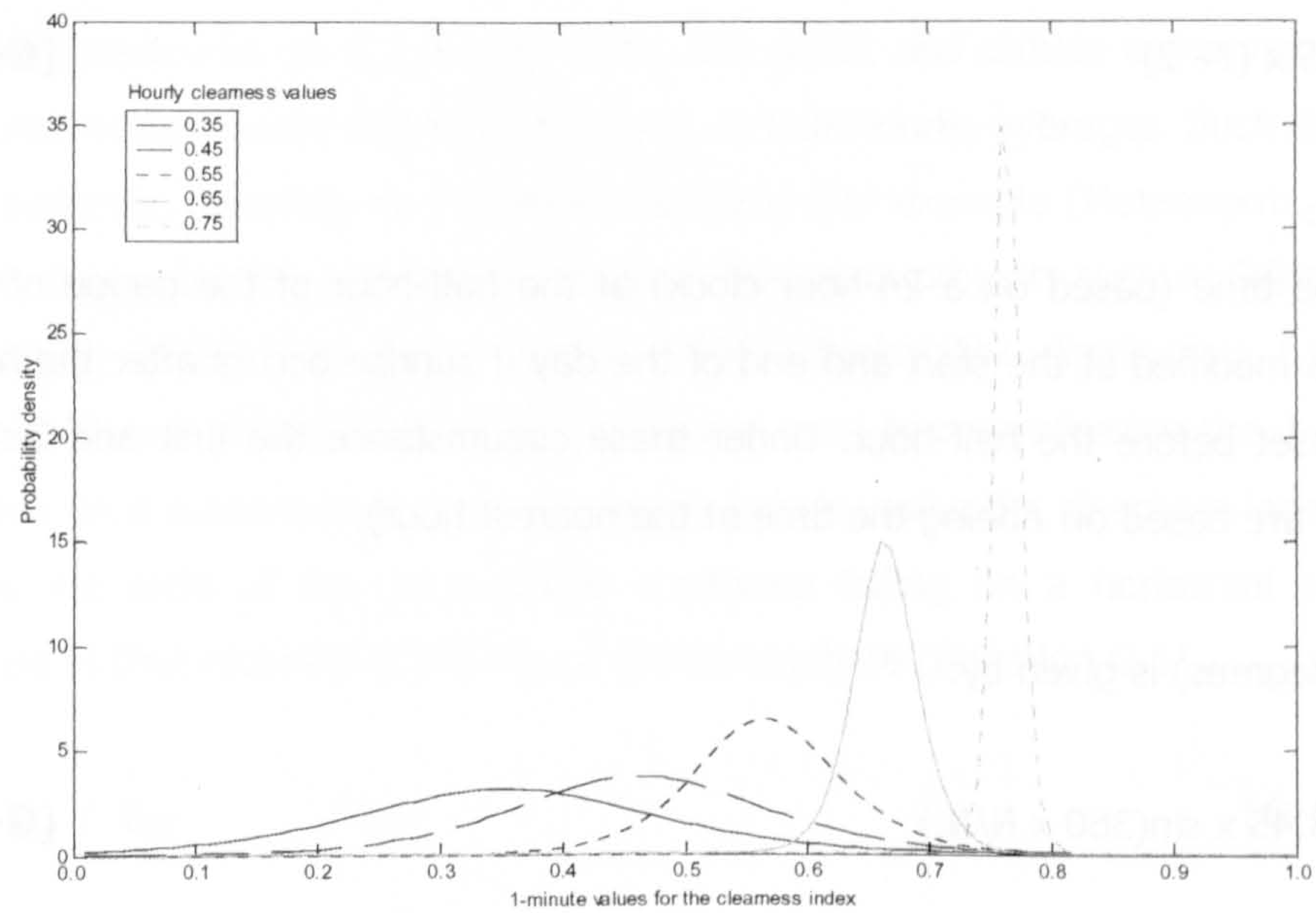


Figure G-1: Probability distributions for the 1-minute values of clearness index, based on hourly values (based on [Torvar et al, 2001])

These distributions suggest that when the hourly clearness index is low, the 1-minute indices vary widely (this will generally occur under cloudy conditions) and when the hourly value is high, the 1-minute values occur over a narrow band (largely cloudless conditions). Using these distributions, 1-minute values for the clearness index may be selected on a random basis and used to estimate the 1-minute averaged global irradiance on a horizontal surface (Equation G-6).

$$E_{eg\_min} = k_{T\_min} \times E_{eg} \qquad \textbf{[G-6]}$$

where:

E_{eg_min} is the 1-minute global irradiance on a horizontal surface (W/m^2)

k_{T_min} is the 1-minute clearness index

The resulting estimate of the solar irradiance is very spiky in nature (Figure G-2).

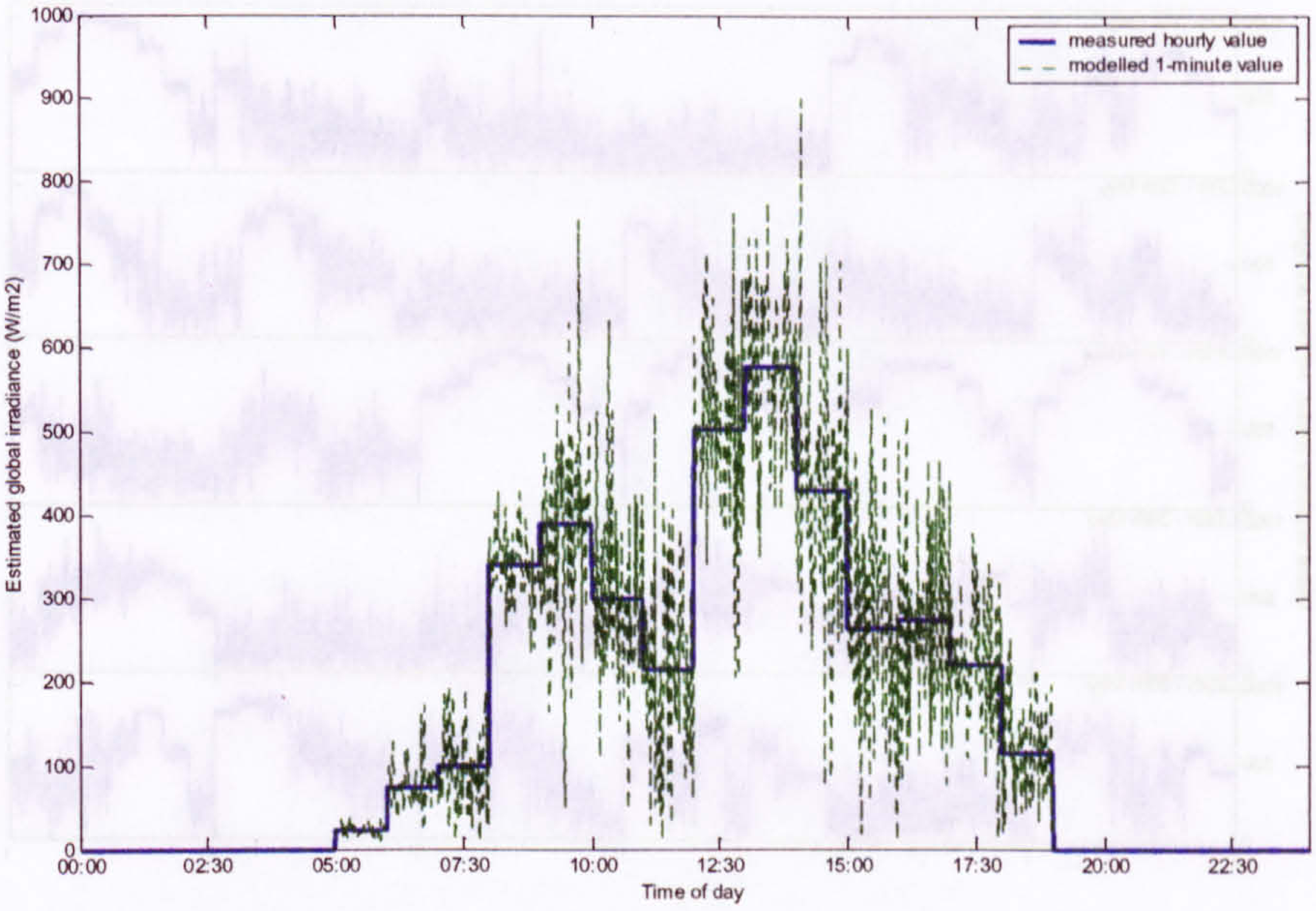


Figure G-2: Modelled values for 1-minute averaged global irradiance compared to measured hourly values (location: Leicester; date: 22-June-2000)

In reality, this represents an over-simplification of the time-varying nature of irradiance since the minute by minute changes are not likely to be completely random. Measurements of 1-minute averaged irradiance on a single day in May are published in a study of daylighting [Walkenhorst et al, 2002]. The example suggests that the irradiance tends to exhibit this highly variable nature during the middle of the day (from around three hours after sunrise until three hours before). At other times of the day, irradiance values appear to rise and fall smoothly.

In a statistical study of irradiation, Glasbey provides half-minute averaged irradiance values for 30 days in May [Glasbey, 2001]. For comparison, the results from the proposed model are provided (as 1-minute averaged irradiances, Figure G-3).

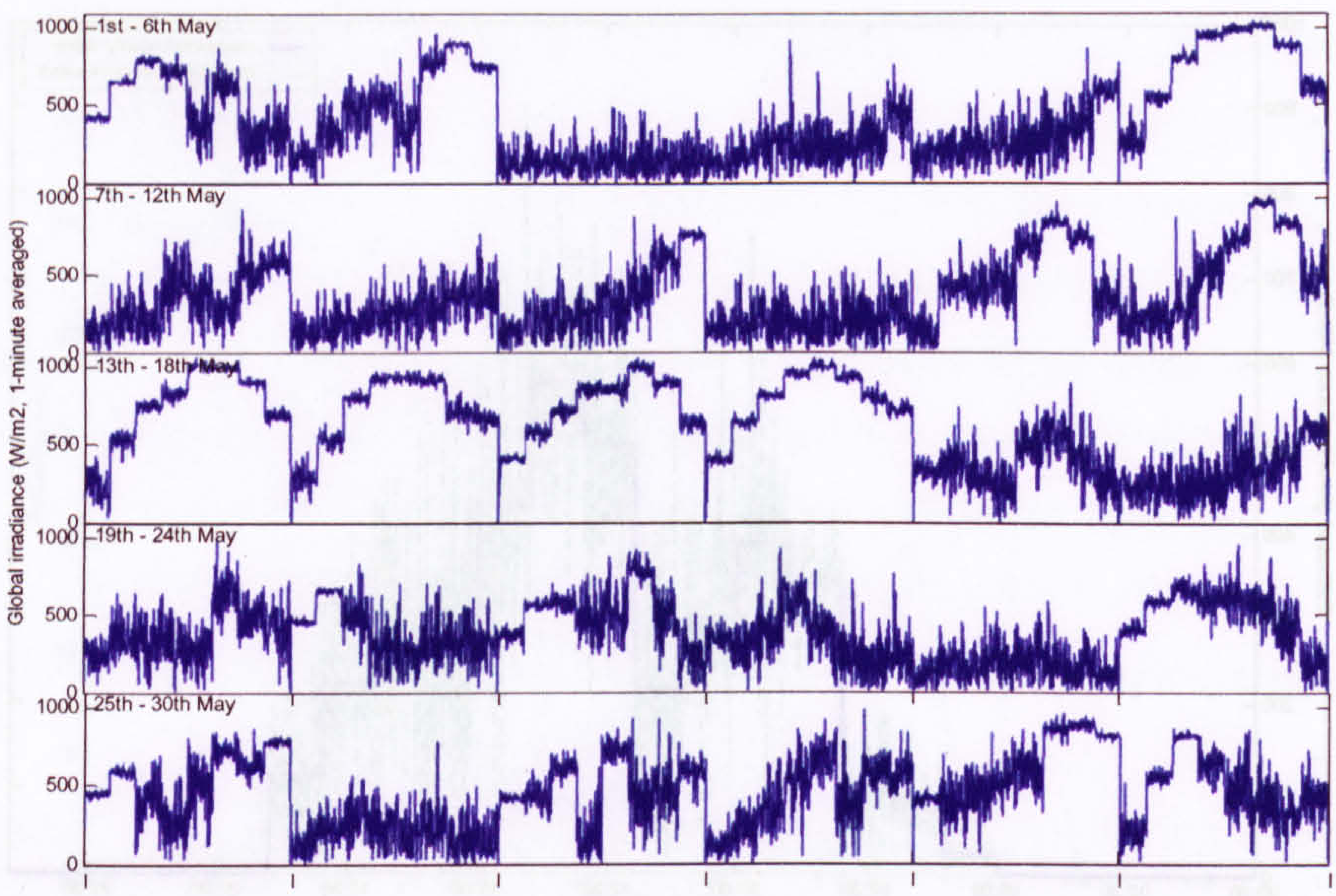


Figure G-3: Modelled 1-minute averaged global irradiance values for 30 days in May (location: Leicester, based on weather data for May,2000)

Compared to Glasbey's data, the model output gives much higher minute by minute variation at low levels of irradiance and too little at high levels, with steps from one hour to the next on clear days. More comprehensive models of solar irradiance include some features of time dependency to mimic the real effects of cloud cover. These include multiprocess dynamic linear models and non-linear auto-regressive processes, which Glasbey reviews in some detail.

The modelled irradiance (based on 2000 weather data) is also compared with 5-minute averaged irradiance data measured in Leicester in 2002 (Figure G-4).

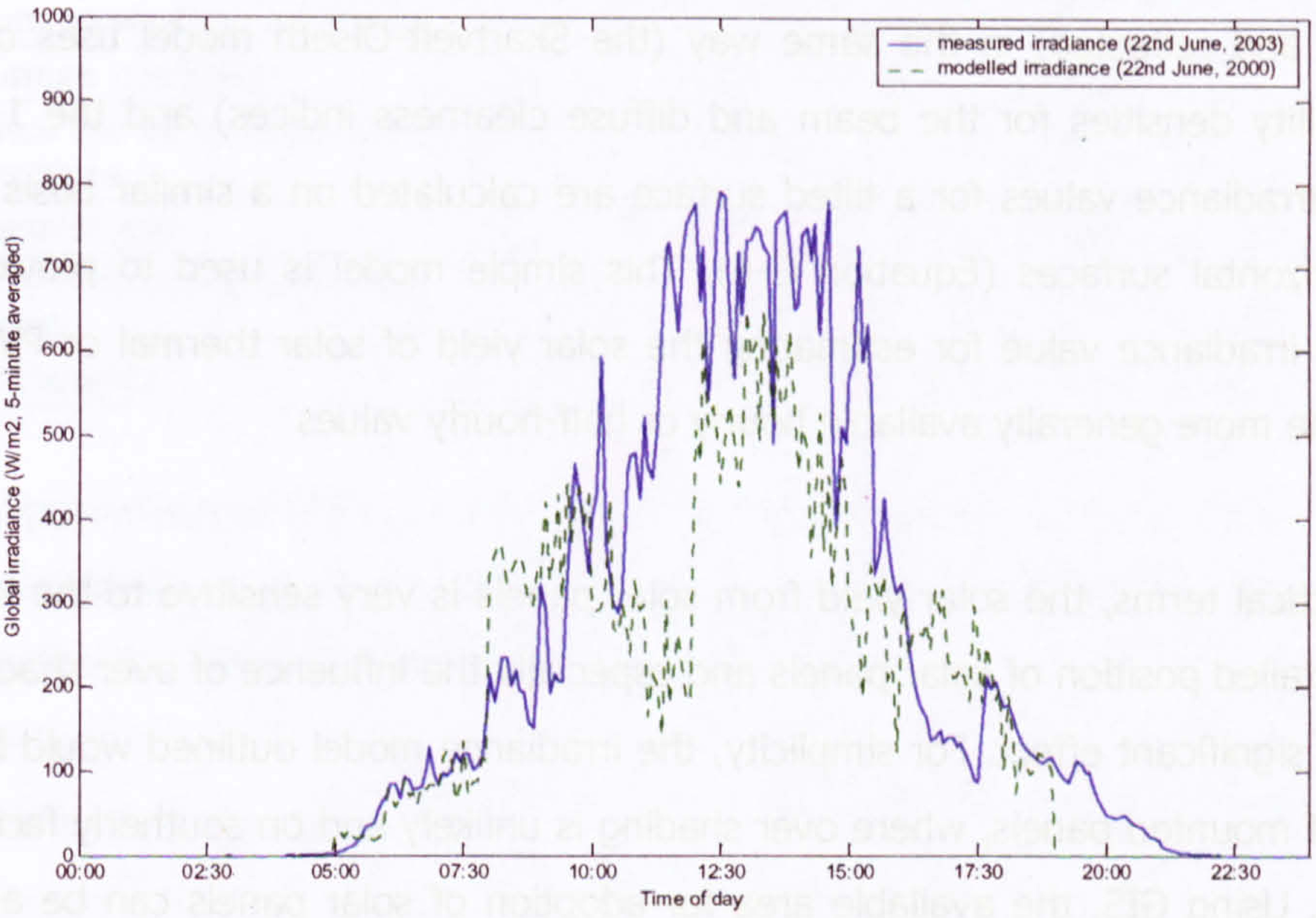


Figure G- 4: Comparison of measured and modelled 5-minute averaged irradiance data (location: Leicester, date: 22nd June - note: measured data relates to 2002 and the modelled data is based on weather data for 2000)

The measured data again displays smoothing just after sunrise and before sunset. However, the modelled data behaves in a broadly similar way and, with some short-comings acknowledged, the outlined basis will be used to illustrate the effect of solar collectors on the demand data. The Skartveit-Olseth method, also based on clearness index variations, (as outlined in [Walkenhorst et al]) or the autoregressive time series developed by Glasbey [Glasbey, 2001] are suggested alternatives for greater accuracy.

G.1.2 Global irradiance for a tilted surface

For a tilted surface, the global irradiance must be adjusted using the orientation (the surface azimuth angle) and the slope of the surface, since these affect the relative angle of the surface to the sun. A third component arises in the irradiance as a result of the energy reflected onto the sloping surface from the surroundings, usually based on an estimate of the diffuse reflectance. A variety of models exist to provide the irradiance of a tilted surface from the values for a horizontal surface (for example the Perez tilted surface model [Perez et al, 1987]). Alternatively, the data from S@tel-Light [S@tel-Light, 2004] can be accessed for different user inputs of orientation and slope using tilted surface models developed within the project.

The 1-minute clearness index is assumed to affect the three components (beam, diffuse and reflected) in the same way (the Skartveit-Olseth model uses different probability densities for the beam and diffuse clearness indices) and the 1-minute global irradiance values for a tilted surface are calculated on a similar basis to that for horizontal surfaces (Equation G-6). This simple model is used to provide a 1-minute irradiance value for estimating the solar yield of solar thermal or PV panels from the more generally available hourly or half-hourly values

In practical terms, the solar yield from solar panels is very sensitive to the location. The detailed position of solar panels and especially the influence of over shading can have a significant effect. For simplicity, the irradiance model outlined would be used for roof mounted panels, where over shading is unlikely and on southerly facing roof spaces. Using GIS, the available area for adoption of solar panels can be assessed and the number of solar panels of standard sizing determined. For the Solar City project individual buildings are linked, in terms of slope and orientation, to a database of irradiance values that are typical for the general location.

G.2 PV yield

G.2.1 Estimating the PV output

Having determined the solar energy falling on a tilted surface, it is possible to estimate the electrical power output from a PV panel. The output is affected by the ambient temperature, which changes the activity of the electrons in the silicon cells of the PV array and the efficiency with which the panel is able to convert solar energy to electrical energy – including that of the power conditioning equipment. For a simple PV model, the basic equation for the hourly output from a solar array, similar to that described by Gadsden [Gadsden, 2001], can be adapted. The input data required by the calculations depends on the specification of the panels used. To provide an example, assumed values have been used, based on the BP Solar Panel, BP585F (Table G-1).

Parameter	Symbol	Assumed value	Units
Maximum power point efficiency	$\eta_{mp,ref}$	13.5	%
Temperature coefficient	μ_{mp}	0.086	V/°C
Reference cell temperature at standard test conditions	T_{ref}	25	°C
Heat transfer rate	$\tau\alpha/U_L$	0.0288	m^2K/W
Efficiency of power conditioning equipment	η_e	0.74	
Area of the array	A_{array}	10.08	m^2

The PV power output (PV_{hourly}, in kW) may be calculated on an hourly basis, from the global irradiance on a tilted surface (E_{eg_tilt}, in W/m^2), the area of the array and the hourly value for the array efficiency, η_i (Equation G-7):

$$PV_{hourly} = \eta_i \times A_{array} \times E_{eg\_tilt}/1000 \qquad \textbf{[G-7]}$$

The hourly value of the array efficiency is related to the operating temperature ($T_{a,i}$ in °C), efficiencies and coefficients associated with the panel specification ($\eta_{mp,ref}$, η_e, μ_{mp}, and $\tau\alpha/U_L$) and the adjustment for variations in the sun position, for a given hour, over the month (Z_i), which is based on an empirical approach developed by Duffie and Beckman [Duffie & Beckman, 1991] (Equations G-8 to G-15)

$$\eta_i = \eta_{mp,ref} \times \eta_e \times [1 + \{\mu_{mp} \times (T_{ai} - T_{ref})/ = \eta_{mp,ref})\} + \{ \mu_{mp} \times E_{eg\_tilt} \times \tau\alpha/U_L \times (1-\eta_{mp,ref}) \times Z_i\}] \qquad \textbf{[G-8]}$$

$$Z_i = (E_{ET}/E_{eg\_tilt})^2 \times (a \times b_1 + a_2 \times b_2 + a_3 \times b_3) \qquad \textbf{[G-9]}$$

and

$$a_1 = R_b^2 + \rho \times (1-\cos\beta) \times R_b + \rho^2 \times (1-\cos\beta)^2/4 \qquad \textbf{[G-10]}$$

$$a_2 = R_b \times (1+\cos\beta - 2 \times R_b) + [\rho \times (1+\cos\beta - 2 \times R_b) \times (1-\cos\beta)]/2 \qquad \textbf{[G-11]}$$

$$a_3 = [\{(1-\cos\beta)/2\} - R_b]^2 \qquad \textbf{[G-12]}$$

$$b_1 = -0.1551 + 0.9226 \times k_{TH} \qquad \textbf{[G-13]}$$

$$b_2 = 0.1456 + 0.0544 \times \log_e(k_{TH}) \qquad \textbf{[G-14]}$$

$$b_3 = k_{TH} \times (0.2769 - 0.3184 \times k_{TH}) \qquad \textbf{[G-15]}$$

The hourly air temperatures are based on the monthly mean daytime air temperatures, which may be obtained from the BREDEM-8 reference tables for twenty-one regions of the UK (or from local climate data). According to previous research [Evans, 1981; Clark et al, 1984] this does not introduce a significant error to the calculated array efficiencies. Finally, the 1-minute values of the PV output can be calculated from the hourly values, using the 1-minute variations in clearness index (Equation G-16).

$$PV_{min} = PV_{hourly} \times k_{T\_min}/k_{TH} \qquad \textbf{[G-16]}$$

On this basis, the PV output may be predicted for a given panel for every day of the year (Figure G-5). Using this method, the model predicts an annual PV electrical output of 2986 kWh assuming forty-eight BP585F solar panels fitted to a 50° sloping roof. By comparison, real data from this installation on the Oxford Solar House [Roaf & Walker, 1997] suggests an annual output of 2937 kWh whilst the output predicted by BP Solar is 3200 kWh.

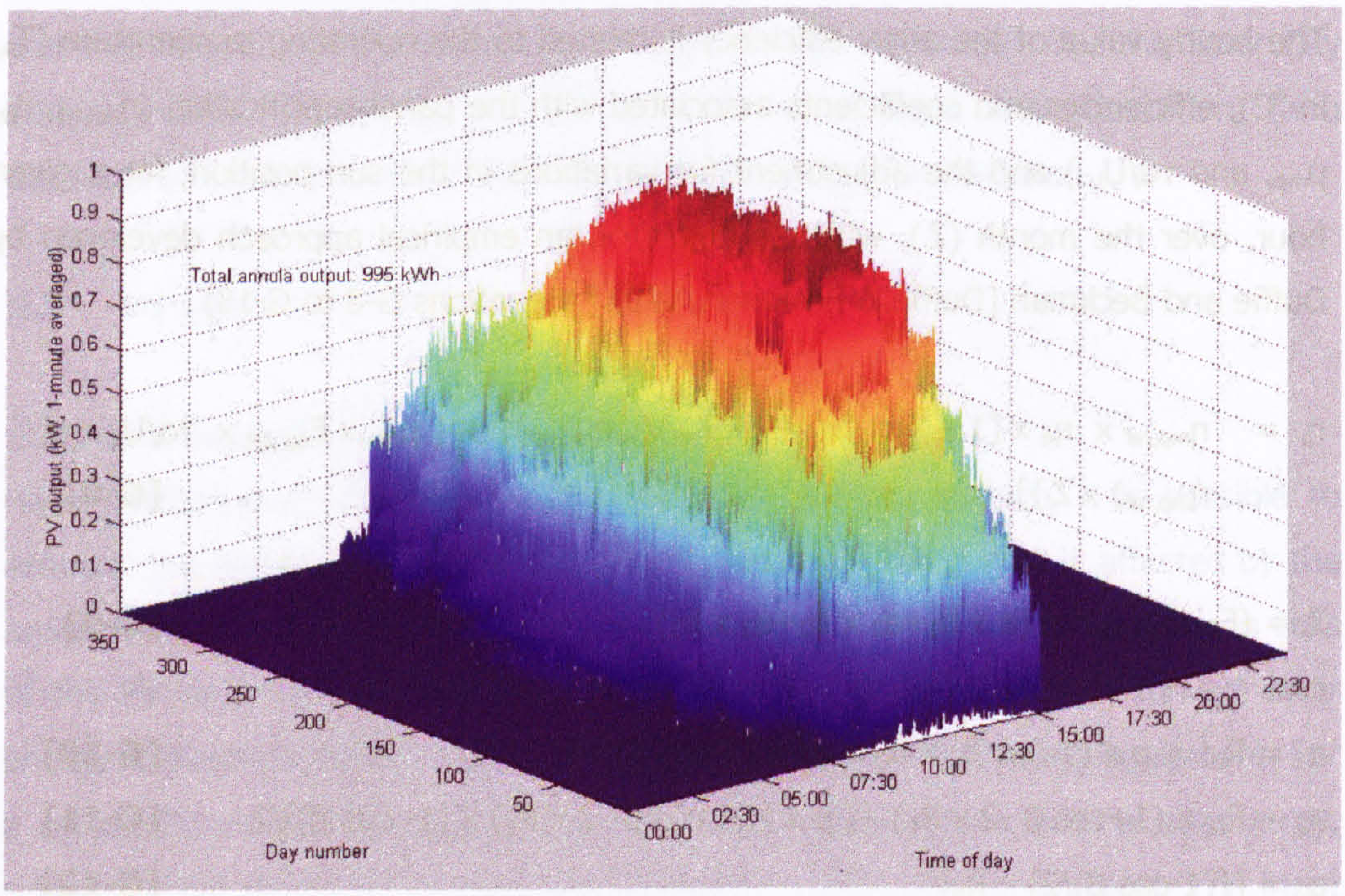


Figure G-5: Modelled 1-minute power output from a PV panel (south facing, 30° tilt, weather data for 2000, 10m² array of BP585F panels)

G.2.2 Effect of the PV output on electrical loading

If the PV output is used instantaneously instead of the grid supply, then the 1-minute value can be simply deducted from the 1-minute electrical demands. If the output is to be stored, then allowance must be made for the efficiency of the storage components and any decay in the stored energy.

Using the PV model with the load models, it becomes possible to examine the energy saving potential in some detail. For example, in a single home, the models suggest that use of $10m^2$ of PV arrays may do little to improve the peak demand but can provide a small net export during mid-day in the summer (Figure G-6). In a small group of varied housing, with a linked PV supply, more of the energy can be used since the demand for the group is smoothed and there a better opportunity for the peak demand to be reduced (Figure G-7). When the community includes non-domestic buildings, it becomes more likely that all the generated PV supply can be used, without much export to the grid. The reduction in the peak demand may not be significantly affected since it depends on the relative timing of the peak demand compared to the PV supply (Figure G-8). This may not be evident when the supply and demand are averaged over a longer time span.

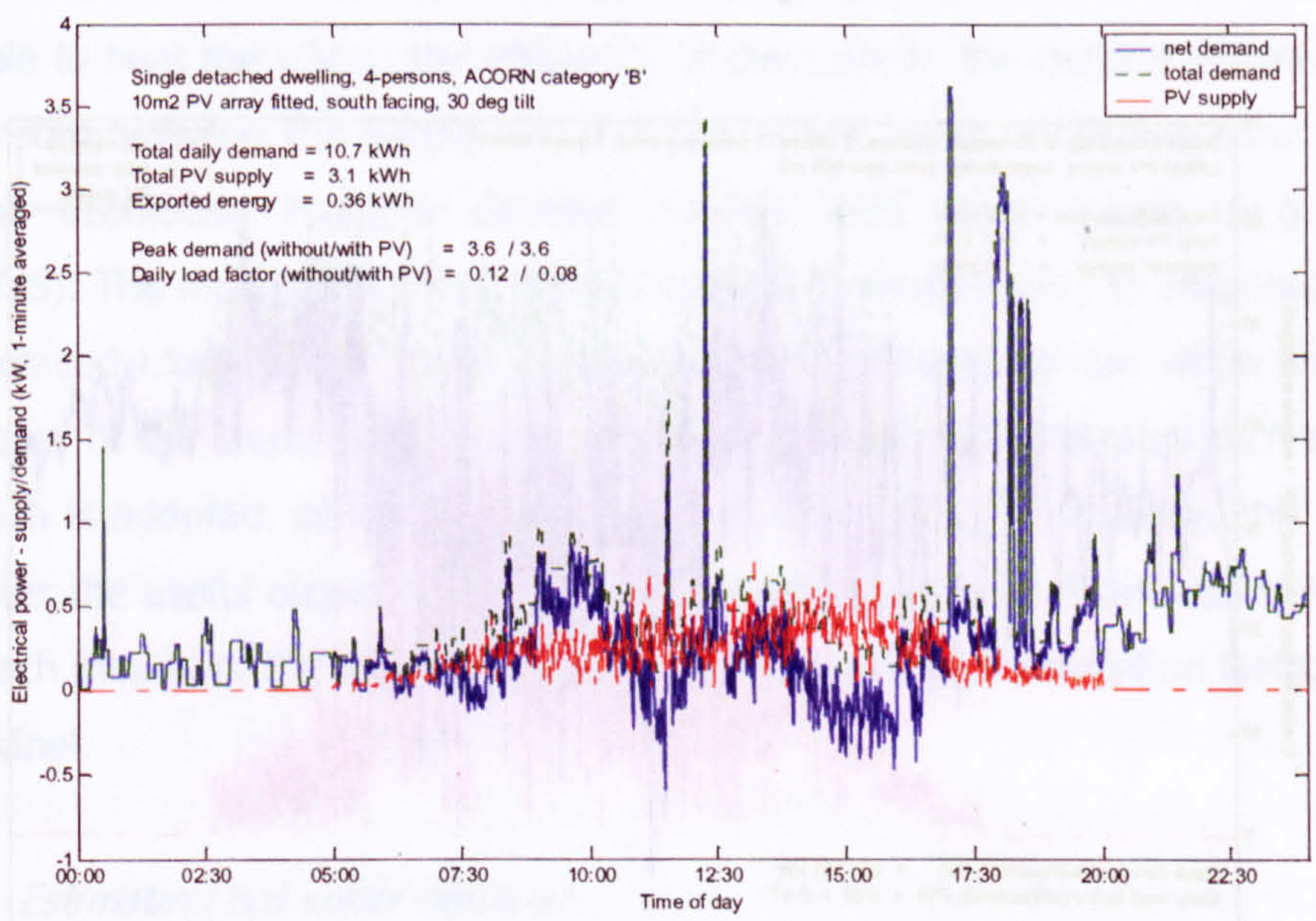


Figure G-6: Example showing modelled estimate of PV supply and electrical demand (gross and net) for a single home, fitted with $10m^2$ of PV arrays (22^{nd} June, 2000)

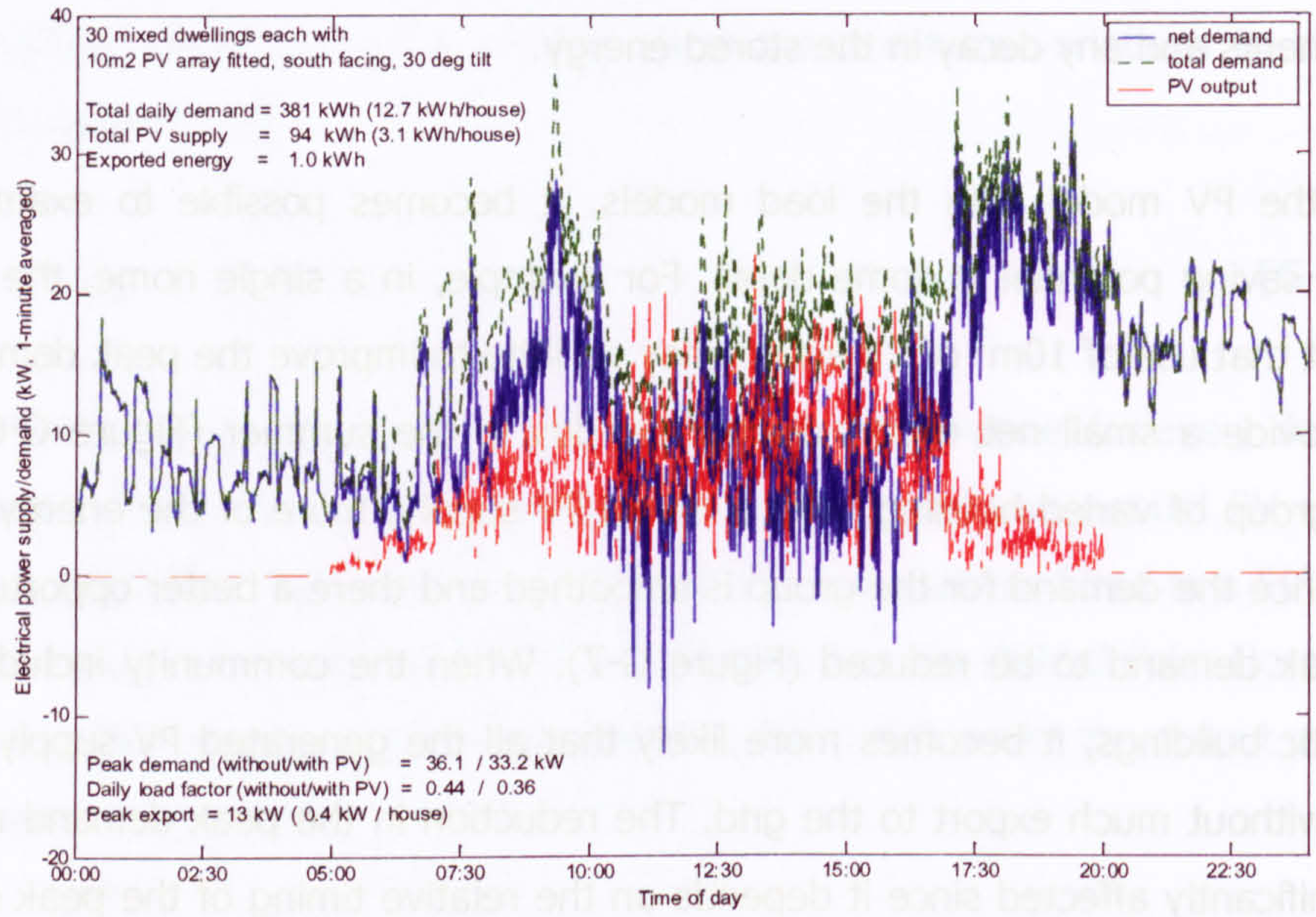


Figure G-7: Example showing modelled estimate of PV supply and electrical demand (gross and net) for a community of 30 different houses, each fitted with 10m^2 of PV arrays (22nd June, 2000)

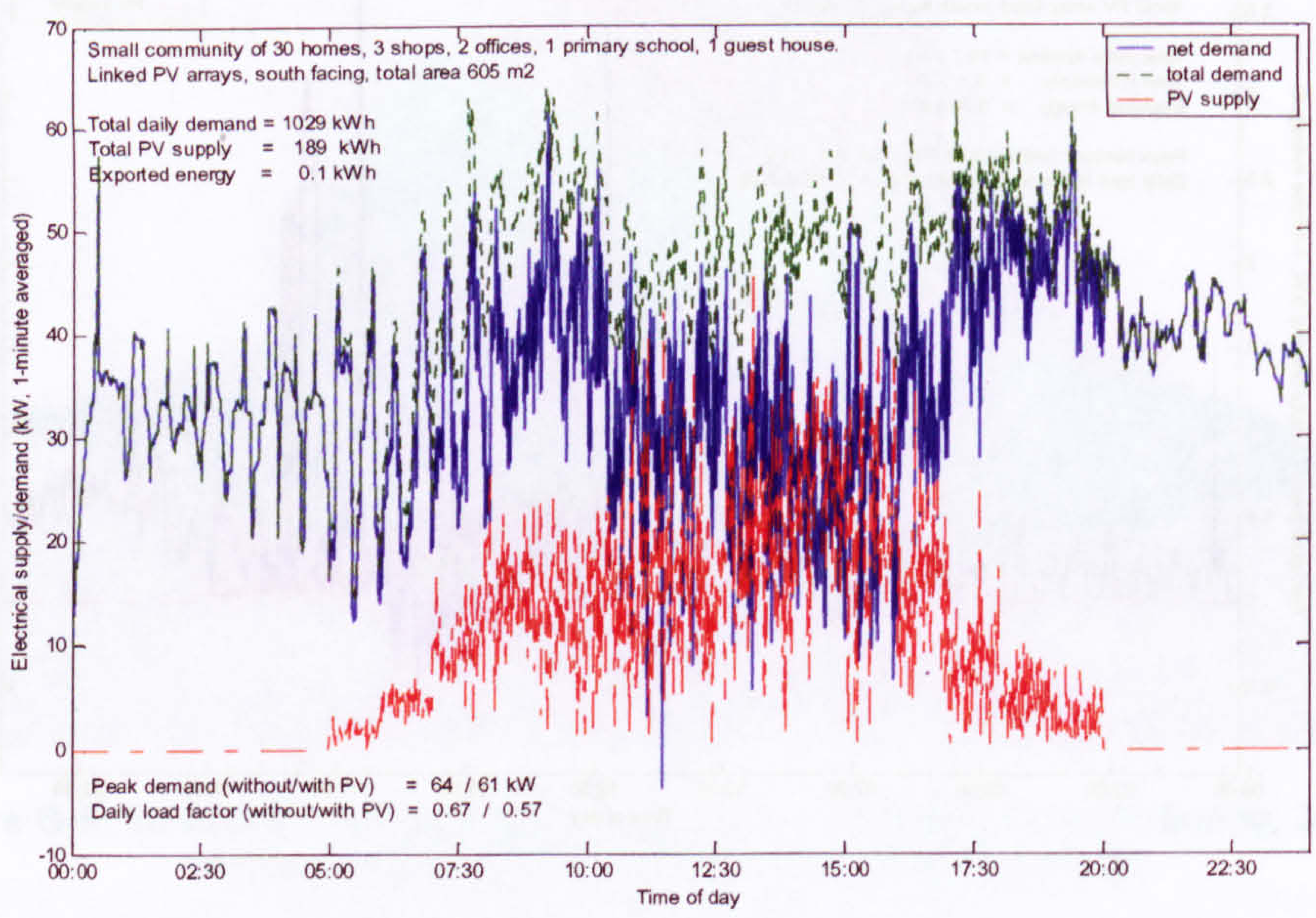


Figure G-8: Example showing modelled estimate of PV supply and electrical demand (gross and net) for a small mixed community with a total PV area of 605m^2 (Monday, 22nd June, 2000)

G.3 Solar thermal yield

G.3.1 General concepts of solar water heating

Modelling the effect of solar thermal panels on the electrical demand is more complicated than that of PV since there is no direct export of power but a modification of the water heating demand. Solar thermal systems used in water heating systems generally operate either by using a single or a two tank system. In both cases, the water heated by solar energy is piped through a heat exchanger to heat water from the cold water tank, thus keeping the solar water system separate from the consumed hot water system. With a single tank system, the heat exchanger is built into the main hot water storage tank, which generally has a back-up electrical immersion heater. To avoid significant modification of existing systems, a two tank approach can be introduced, where the heat exchanger is contained in a separate tank, from which water is fed into the bottom of the main storage tank.

To model the effect of the solar panel requires representation of the solar energy available to heat the water, the efficiency of the system, the thermal losses and the relationship between the supply and demand of hot water. Modelling solar thermal systems accurately requires detailed models with many inputs (e.g. ESP-r, TRYNSYS). The majority of these models operate from an hourly to an annual basis. Fine detailed modelling of the solar thermal yield is inappropriate when compared with some of the crude assumptions made in the load models and as such a simple approach is adopted, based on Gadsden [Gadsden, 2001]. Essentially, this method estimates the useful output from a solar panel per annum and distributes the energy over each minute of the day, using the relative proportion of irradiation falling on the solar panel.

G.3.2 Estimating hot water demand

The daily demand for hot water (V_{water} in litres) is assumed to follow the BREDEM-8 calculation (Equation G-17), which relates water demand to the number of occupants (N). Gadsden showed that an optimum volume for storage of the solar heated water (V_s in litres, either in a separate tank or as part of the primary storage tank) was 1.7 times the daily volume of hot water required (Equation G-18)

$$V_{water} = 38 + 25 \times N \qquad \textbf{[G-17]}$$

$V_s = 1.7 \times V_{water}$ **[G-18]**

The storage parameter, R, is effectively the number of days for which the hot water demand could be provided by the stored solar heated water (Equation G-19).

$R = V_s/V_{water}$ **[G-19]**

The daily energy demand, L_{water} (MJ/day), for water heating can be derived (equation G-20) from the assumed volume of hot water required and the difference between the desired hot water temperature, T_{hot} (in °C, generally assumed to be 60°C, to avoid problems from Legionnaire's disease) and the temperature of the incoming supply water, T_{cold} (in °C, which for annual calculations can be assumed to be 2°C above the mean monthly temperature, provided by the BREDEM-8 model).

$L_{water}=0.00418 \times V_{water} \times (T_{hot}-T_{cold})$ **[G-20]**

This is used to provide an estimate of the annual energy demand for hot water.

G.3.3 Estimating the required area of the solar collector

The next step is to determine the area of the solar heating panel, which in the UK is generally sized to supply the entire hot water demand during June. This tends to give a realistic return on investment, balancing installation costs against energy savings. The output of the solar collector depends on the design and the performance of the different types of collector is generally quoted as the area required to heat 40 litres of water (a typical daily demand per person) during June to the desired temperature. This area, $A_{thermal}$ (in m^2), varies from $0.75m^2$ for evacuated tube models to $1.75m^2$ for unglazed panels. A value of $1.0m^2$, typical of advanced plate type collectors, is adopted for this model. The theoretical area required for the solar panel, A_1 (in m^2), is estimated from the assumed hot water demand (Equation G-21).

$A_1 = A_{thermal} \times V_{water}/40$ **[G-21]**

This theoretical value is used to select the number of panels needed. Panel sizes in practice vary from around 1.2 to 2.2 m^2. For the purposes of this model, a

Thermomax THS 400 collector is assumed to be installed, which has a unit area of $2.14m^2$. For a family of four people, the daily hot water demand would be approximately 138 litres per day (equation G-17), requiring a theoretical area of $3.45m^2$ (equation G-21) which can be achieved with two Thermomax advanced plate collectors, giving an actual area, A_2, of $4.28m^2$.

G.3.4 Collector performance

The next stage of the calculation is to determine the effectiveness of the collector. The collector performance parameter, K, relates the collector losses to the collector gains (Equation G-22).

$$K = [U/\eta_o \times (T_{hot} - T_{cold})] \;/\; [G_{tilt} + (U/\eta_o) \times (T_{air} - T_{cold})] \qquad \textbf{[G-22]}$$

where:
U is the collector heat loss coefficient (in W/m^2K)
η_o is the zero loss collector efficiency
(The value for U/η_o is 1.34 W/m^2K for the Thermomax THS 400).

G_{tilt} is the annual mean of the daily peak irradiation (W/m^2) falling on the tilted surface. For the purposes of this study, the data provided by the S@telLight project has been used.

T_{air} is the mean daytime air temperature (°C)
(assumed to be 1°C above the monthly mean temperatures given by BREDEM-8)

Other non-dimensional parameters, F, B and λ, are required for the panels, calculated from the storage parameter, R, and collector performance parameter, K, using empirical relationships (Equations G-23 to G-26) from annual simulation results [Kenna, 1984].

$$F = 0.554 + 0.342 \times R - 0.097 \times R^2 \qquad \textbf{[G-23]}$$
$$B = 0.383 \times K - 0.066 \times K^2 \qquad \textbf{[G-24]}$$
$$\lambda = 1.121 + 0.212 \times K \quad \text{for } K \leq 1 \qquad \textbf{[G-25]}$$
$$\lambda = 0.71 \times (1 + K) \quad \text{for } K > 1 \qquad \textbf{[G-26]}$$

G.3.5 Solar-thermal panel energy output

The collector sizing parameter, M, is the ratio of the solar energy available compared to the hot water energy demand (Equation G-27).

$$M = A_2 \times [H_{tilt} + 0.0432 \times (U/\eta_o) \times (T_{air}\text{-}T_{cold})] / L \qquad \textbf{[G-27]}$$

where H_{tilt} is the annual mean value of the daily mean irradiance (MJ/m^2) on the tilted surface.

The total annual solar energy supplied to the hot water system, Q_{annual} (MJ per annum) can then be calculated (Equation G-28).

$$Q_{annual} = N_y \times L \times (F - B) \times (1 - e^{-\lambda M}) \qquad \textbf{[G-28]}$$

where N_y is the number of days in the given year.

The solar energy supplied per minute (Q_{min}, MJ/min) is then assumed to be in the same proportion to the annual solar energy supplied as the irradiation on the tilted surface in the same minute compared to the total annual irradiation (Equation G-29).

$$Q_{min} = Q_{annual} \times [(E_{eg\_min\_tilt}/60)/(\sum_{1}^{Ny*24} E_{eg\_tilt})] \qquad \textbf{[G-29]}$$

The solar energy supplied per minute can be related to the 1-minute averaged power level (H_{min}, kW) using a factor of 3.6 to convert from MJ to kWh and 60 to convert from kWh to kW per minute (Equation G-30).

$$H_{min} = Q_{min} \times 60/3.6 \qquad \textbf{[G-30]}$$

G.3.6 Reduction of electrical water heating demand

The domestic load model calculates the estimated water heating demand on a 1-minute basis (refer to section 6.4). When power is available from the solar collector, the electrical demand is assumed to be reduced. If there is excess power from the solar collectors, it is assumed that this will remain stored and may be used to reduce future electrical demand (i.e. the model assumes perfect lagging of the hot water tank).

G.3.7 Validation of the solar-thermal model

Whilst founded on a simple basis, the solar thermal appears to provide reasonable results. For a single test-run of the model, assuming a 4-person household, the model predicts an annual total for the useful solar energy supplied from two Thermomax THS400 panels on a south facing roof with 30° tilt of 1882 kWh/year (this value varies since it is based on the sum of the values of H_{min} which includes random values for the 1-minute clearness index). SolarMaster 2.01 [Thermomax, 2004] is a software tool, developed by Thermomax and freely available over the Internet. It uses a statistical method for calculating the theoretical solar irradiation together with monthly measured average values to simulate a daily divergent total irradiation at fifteen minutes intervals. SolarMaster estimates for a similar case (using measured weather datasets for Cambridge, UK) an annual supply of 1881.5 kWh. The monthly comparison of the model results and that for the SolarMaster software (Figure G-9) shows a slight under-estimate for the autumn months and over-estimate for the summer months (this may be due to variations in the measured data-sets used, due to cloud cover). In general, the model appears to provide broadly realistic results.

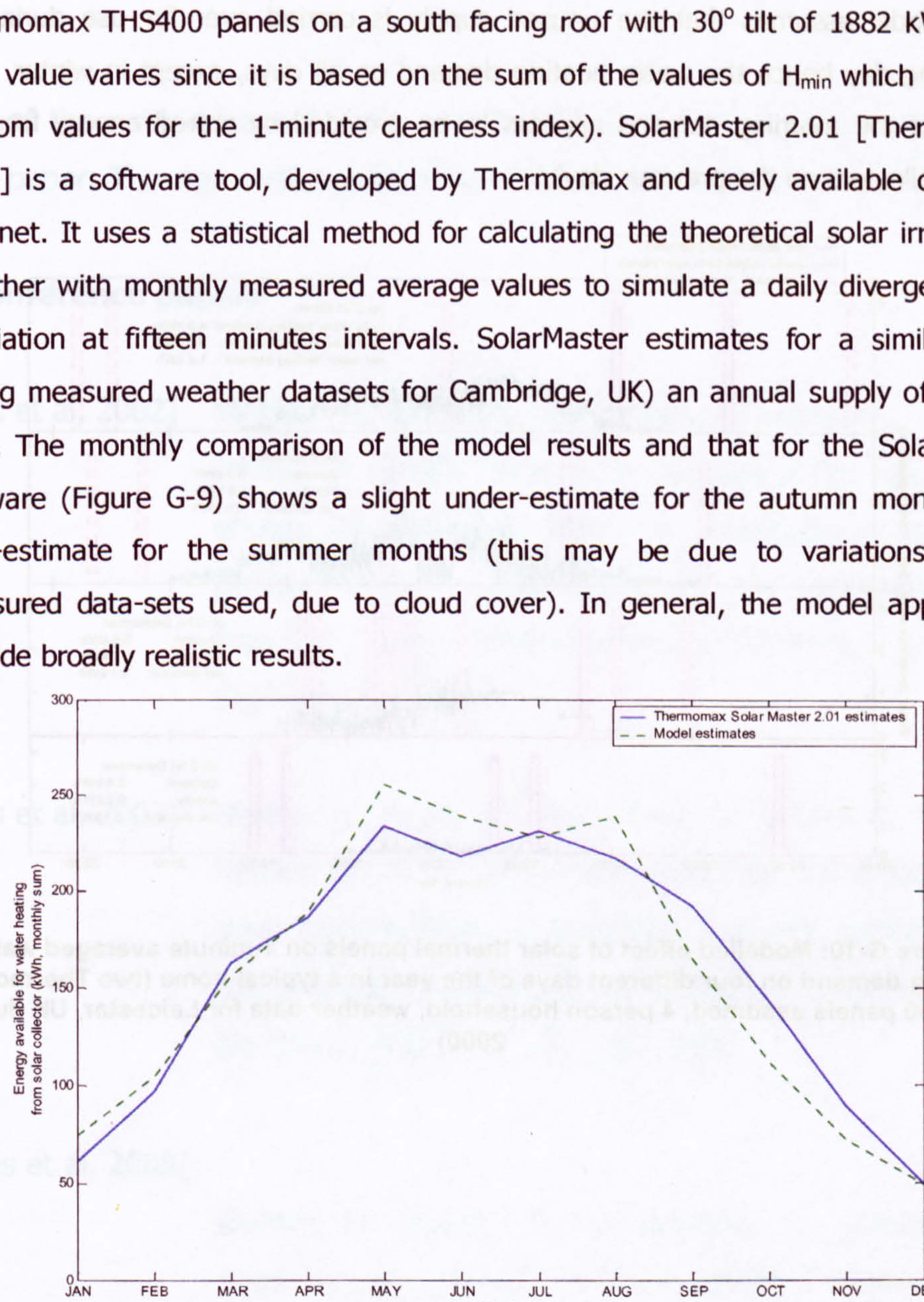


Figure G-9: Comparison of output from the model and from Thermomaster's SolarMaster v2.01 tool for useful energy from a solar thermal collector (assumed south facing, suitable for 4-person household, weather data for Leicester, 2000 used in model and for Cambridge used in Solarmaster tool)

When used at the 1-minute level to adjust the calculated water-heating demand, the model for example shows (Figure G-10) that the entire water heating demand in a 4-person home (unrestricted tariff) can be supplied by the solar collector on a June day. On a spring or autumn day, some of the water demand can be supplied from the solar collector whilst in the winter, virtually all the demand appears as an electrical load. This example illustrates that understanding the relative timing of the supply and demand is important to estimate the real net demand for water heating (the model assumes that the unused supply is carried over for use during the following day hence the water heating demand on all days, except in winter, some or all of the morning demand appears to be provided by stored energy from the solar collectors on the previous day).

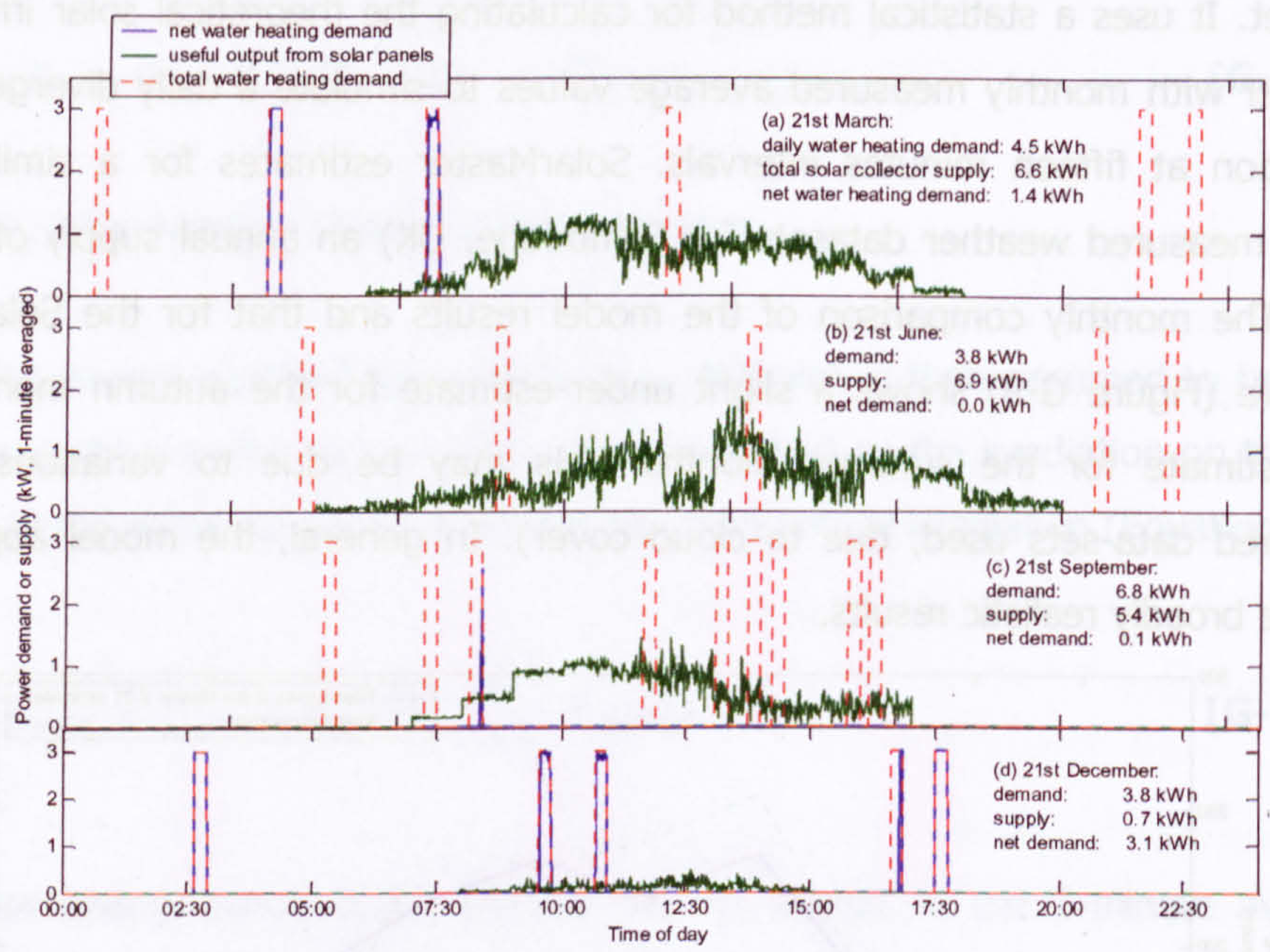


Figure G-10: Modelled effect of solar thermal panels on 1-minute averaged water heating demand on four different days of the year in a typical home (two Thermomax THS400 panels assumed, 4 person household, weather data for Leicester, UK during 2000)

Appendix

H

Published work

Details of the work described have also appeared in conference proceedings and a journal paper. This appendix provides the references and published material.

H.1 Conference papers

[Stokes et al, 2002] Stokes, M, Rylatt, M, Mardaljevic, J, Lomas K, Thomson, M, Infield, D (2002) 'Solar City: managing the uptake of solar energy technologies from an electrical supply network perspective', 5th Symposium of the International Urban Planning and Environment Association, Oxford, UK, September, 2002

[Stokes et al, 2003] Stokes, M, Rylatt, M, Mardaljevic, J, Lomas K, Thomson, M, Infield, D (2003) 'Solar City: assessing the detailed effect of solar technologies on electricity network performance', 17th International Conference on Electricty Distibrtuion, CIRED, Barcelona, Spain, 12th-15th May, 2003

[Stokes et al, 2003]

Stokes, M, Rylatt, M, Mardaljevic, J, Lomas, K (2003) 'Predicting the Effects of Grid-Connected Photovoltaic Power Generation in Complex Urban Environments', PLEA 2003: The 20th Conference on Passive and Low Energy Architecture, Santiago, Chile, 9 - 12 November 2003

[Thomson at al, 2003]

Thomson, M, Infield, D, Stokes, M, Rylatt, M, Mardaljevic, J, Lomas, K (2003) 'Secondary Distribution Network Power-Flow Analysis', IASTED International Conference on Power Generation and Renewable Energy Sources (PGRES '03), Palm Springs, USA, 24^{th} – 26^{th} February, 2003

H.2 Journal paper

[Stokes et al, 2004]

Stokes, M, Rylatt, M, Lomas, K (2004) 'A simple model of domestic lighting demand', *Energy and Buildings*, Vol. 36 (2004) pp 103-116.

Solar City: managing the uptake of solar energy technologies from an electrical supply network perspective.

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Abstract: This paper introduces a new approach to modelling the impact on the electricity supply network of both the embedded generation and the delivered energy replacement that will accrue from the uptake of solar energy technologies. It describes a disaggregated load model - based on patterns of heating, lighting and appliance usage - linked to a Geographical Information System that will be customised to support the estimation of available and supplied solar energy, the visualisation of low voltage networks and the analysis of load flows. The potential of this tool is shown for scenario-based risk assessment of renewable energy projects and programmes by local authority planners working with distribution network operators.

1. Introduction

It is widely recognised that the energy systems of the 21st century must conform to low-carbon policies if serious global warming is to be averted. Solar energy technologies should therefore see greatly increased application. For the electricity industry however this outlook entails possible risks that need to be assessed. The likely scale of these risks depends on which scenario for the adoption of clean energy is most prescient. If, for example, a highly decentralised energy system emerges, the consequences of localised generation associated with solar and other new energy technologies could be far-reaching. Even for more cautious levels of adoption however there remains a need to assess the technical and commercial impacts. The Solar City project and in particular SEnTIENT (Solar Energy Technology: Impact on Electricity Networks Tool), aims to provide support for distribution network operators (DNOs) and Local Authority (LA) planners attempting to foresee the effects of urban solar energy schemes at various scales of uptake. The project, which reaches completion in 2004, involves partners from academia, LAs and DNOs and is primarily targeted at the UK, although the underlying concepts may be applicable internationally.

SEnTIENT will incorporate a number of innovations, currently under development or refinement, to enable diverse aspects of the problem to be addressed effectively. These include a new disaggregated end-use load model, a technique for accurately calculating and visualising the available solar irradiation - and hence the supplied solar energy - and advanced load flow analysis software linked to an interactive low-voltage (LV) network image in a Geographical Information System (GIS). The suite of software will provide a more comprehensive, integrated and problem-specific approach than previously available. This paper provides an overview of the proposed SEnTIENT system and briefly introduces other elements of the tool. Some essential background for understanding the nature of the possible technical problems in the LV networks is provided, earlier important work in this area is reviewed and the conceptual basis of the SEnTIENT load models is described. The paper concentrates on the load models and concludes with a discussion of possible scenarios of use.

2. Overview of the SEnTIENT system design

The GIS interface, based on MapInfo, will allow the user to visualise the network lines, nodes, switches and consumer connection points. The user will have the facility to query features of the network, both physical (line lengths, conductor types, etc.) and performance-related (maximum voltage, overheating, etc.). The interface will provide supportive access to the demand predictions for each consumer as well as the facility to change the basis of the load models, to simulate life-style changes or energy saving strategies for example, or to alter the degree of assignment of solar panels to the consumers in the network area. Because the database and GIS interface are dynamically linked, the user will be able to take simultaneous advantage of the more sophisticated relation database functionality and the spatial data processing and visualisation capabilities of the two software technologies: to give a simple example, selection of a consumer identity in the database will highlight the corresponding location on the map.

As shown in the block diagram (figure 1), the core of SEnTIENT is represented by dynamically linked customised GIS and database applications. These manage the spatial and aspatial data stored in the underlying database, and together provide a flexible interface for the deployment of the main modelling and analysis tools:

- a load flow tool;
- a set of fine-grained load models;
- an advanced irradiation mapping tool.

The irradiation-mapping tool known as ICUE [1] operates on photogrammetry-based 3D city models. It provides both accurate visualisation, using false-colour imagery, and automatic look-up of irradiation values to support selection of appropriate sites for solar panels. Refinements to the tool will enable the supplied solar energy to be estimated automatically on the required time-scale using a simplified sky model and input to SEnTIENT's PV and solar-thermal models. The outputs from these will be used to provide predictions of embedded generation and modified electrical demand.

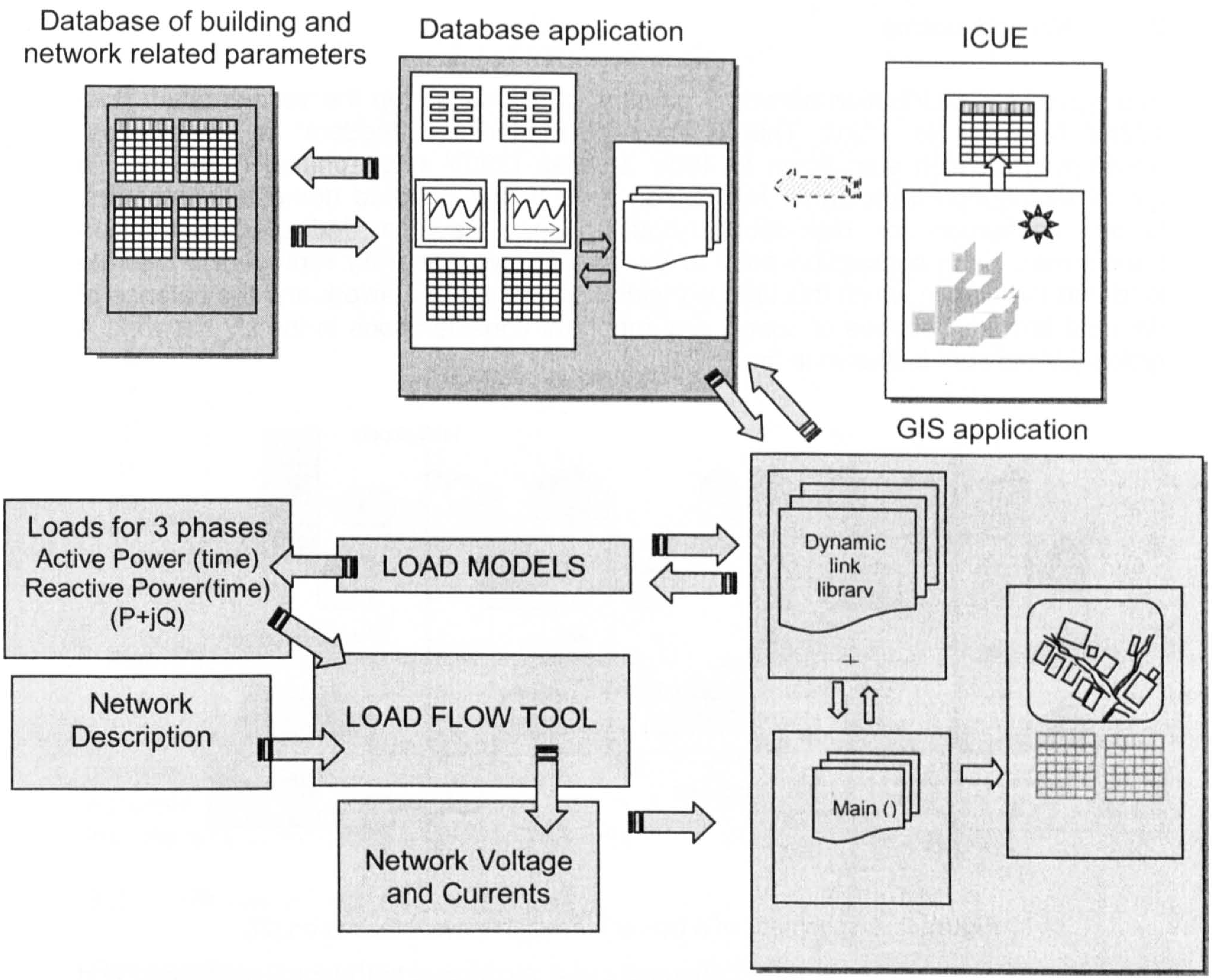

Figure 1: System design block diagram of the SEnTIENT tool

The network performance tool will provide an analysis of the unbalanced 3-phase LV network, taking account of the time-varying active and reactive power flows. There are currently few tools available that provide such detailed analysis of the LV end of the distribution network. The tool will identify local areas of concern – such as overheating – that the user can investigate further within the GIS. The SEnTIENT tool will also provide reports that include features of performance such as peak and average voltages or duration of operation outside of limits. The user will have the facility to make simple changes to the network description in order to compare the performance of alternative designs.

The final element of the package, the load models, will be described in further detail in section 4. In the next section, the background to load modelling is described together with a brief review of previously applied techniques.

3. Background: Load Modelling

3.1 Network basics

In a typical UK distribution network, "primary" substations step the voltage down from 132kV or 33kV to 11kV. This is then distributed on "feeders" to "distribution" transformers, which step down to 400V 3-phase (230V single-phase). In cities, a typical distribution transformer might feed around one hundred domestic customers. Larger consumers or high-density housing may have a dedicated distribution transformer. Each connection point to the network will generally represent a discrete load and the way in which this load is distributed within the network and the balance of demand between phases of supply are important considerations in the LV network. A typical LV network is shown in figure 2.

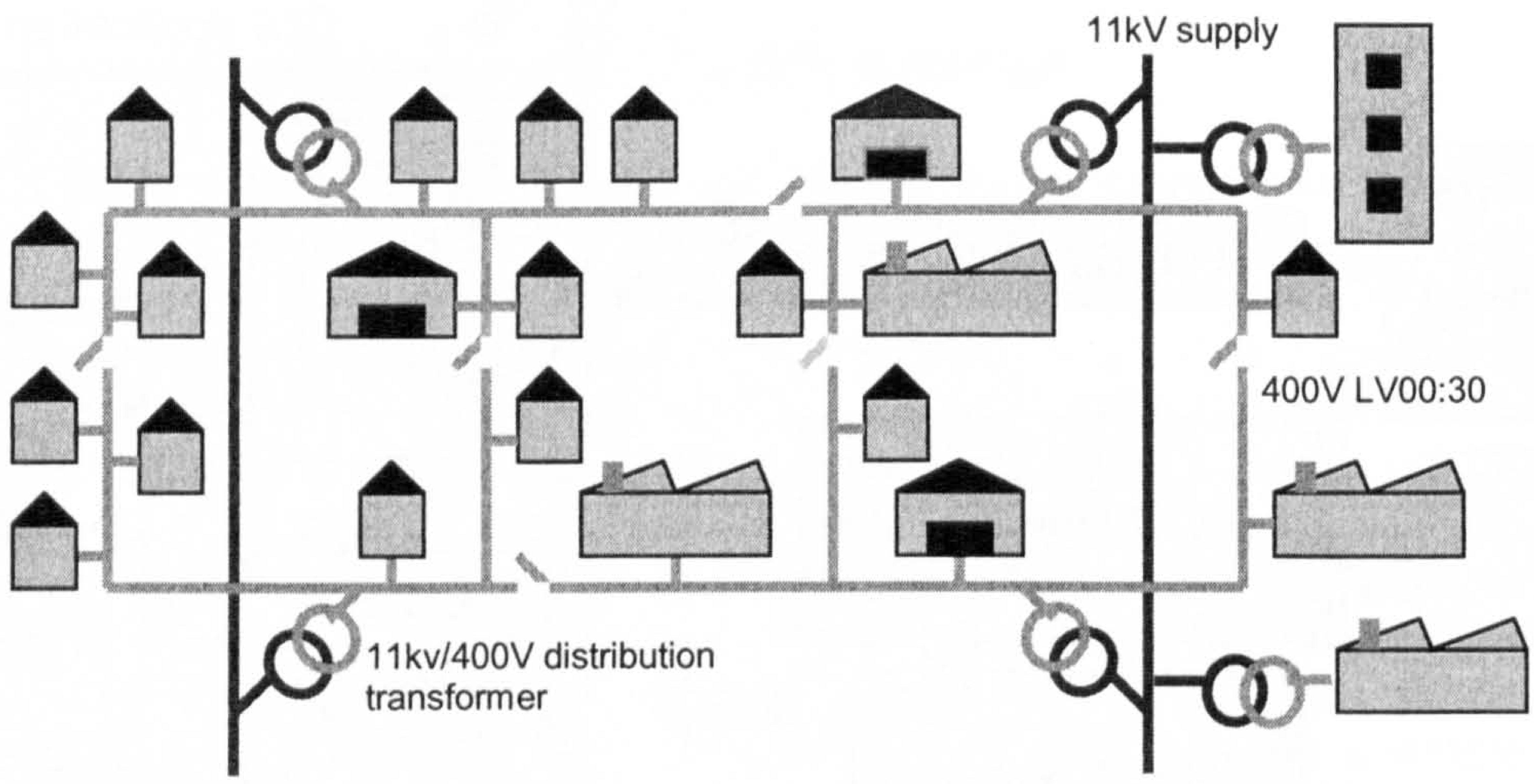

Figure 2: A schematic of a typical LV radial network (based on [2])

The demand across a network of consumers is a mixture of both highly correlated and uncorrelated components. Most domestic consumers will make higher demands during the morning and evening, when the home is occupied. This pattern tends to dominate the daily load profile. The effects of weather and seasonal patterns generally affect all consumers in a similar fashion, especially at the macro level (figure 3). However, for robust LV network design, it is important to look at the micro level – the individual consumer – and then the random components of demand become very important. Of course individual consumer loads are much more stochastic than the aggregated loads seen at the primary substations and, consequently, require much more detailed modelling.

The load profiles (figure 3) show demand averaged on a half-hourly basis, which is the UK norm for scheduling and trading purposes. To represent the diversity present in LV networks, the SEnTIENT tool will be able to predict loads at a much smaller time step, typically one-minute. For short term averaging, the individual load profiles become much more spiky in nature and are more difficult to predict, underlining the need for a stochastic element in the model.

The estimation of individual load profiles gives a far better representation of the distribution of load in the network than approaches based on analysis of aggregated demand at the primary sub-station. It provides a method of accounting for diversity that is closer to reality and it also allows consideration of phase imbalance since the loading of each phase of the LV network can be investigated. It is also useful to

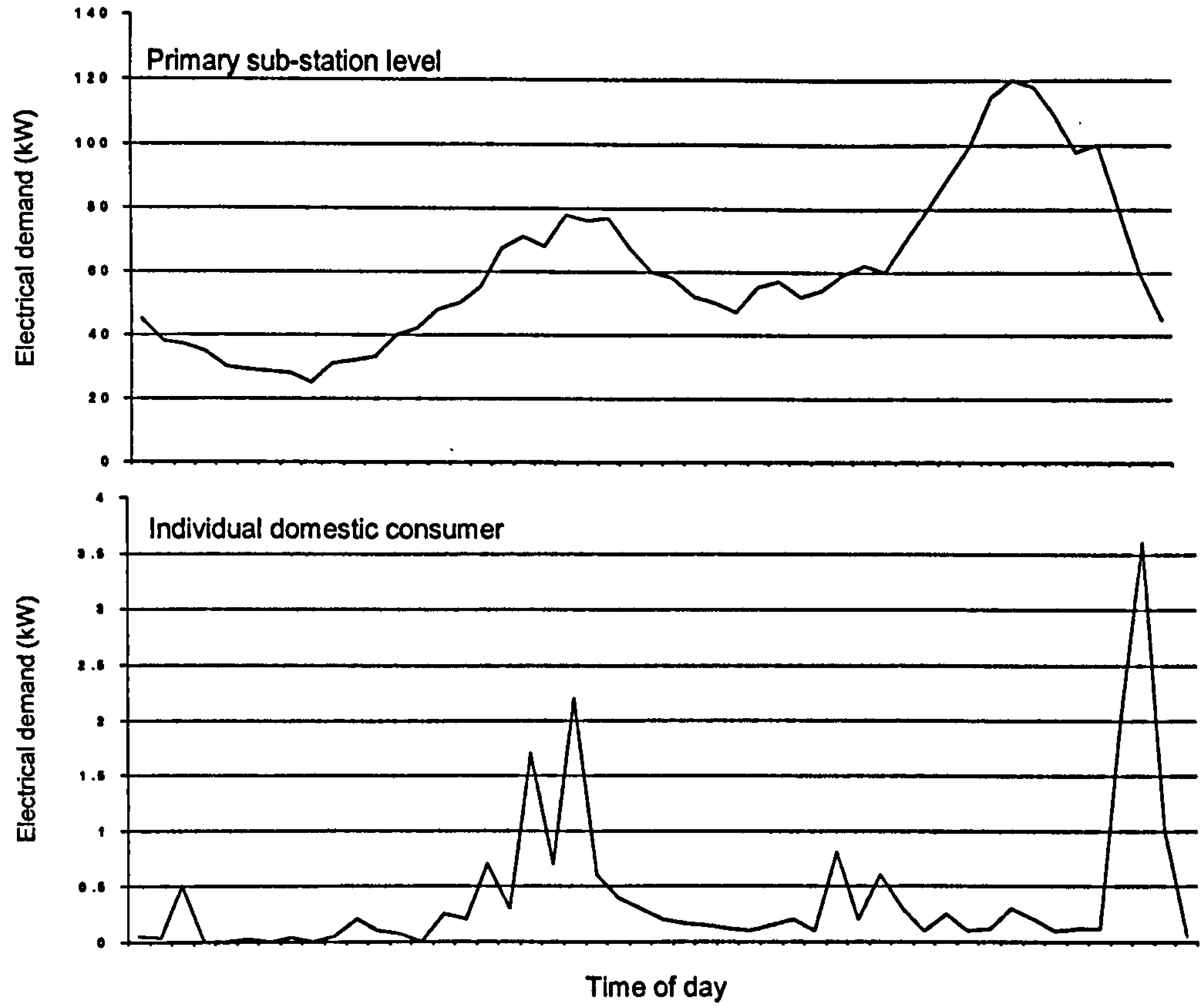

Figure 3: Typical half-hourly load profiles at the primary sub-station and individual consumer levels over a 24 hour period starting at midnight

consider the nature of the appliances being used to create the load – providing an accurate representation of both the active and reactive loads, and facilitates studies into the way in which electricity may be saved in homes and businesses.

3.2 Review of load prediction methods

The simplest method for assigning a load prediction for an individual consumer is to use empirically based values for peak and average demand. In fact, many existing LV circuits were developed on this basis and are consequently over-engineered. For aggregating demand over a group of consumers, because of the diversity of individual demand, the peak and average values have to be factored down – using a diversity factor which decreases with the number of consumers in the group. A recent survey in New Zealand [3] found that many companies still use these simple methods for network design and that values for diversity and demand estimation vary widely.

Arvidson [4] acknowledged that different end-uses of electricity have different relationships with variables such as the weather, built-form and building materials. Consequently he derived a simple model for nine different end-uses, including refrigeration, cooking, etc. The model provided daily profiles of use patterns. Consumer demand for a given end-use could be derived from an hourly variation factor, an estimated peak demand and a diversity factor, which varied with the number of connections on the network. The three values could be changed to account for different occupant behaviour, location, etc.

Increasingly powerful computers have enabled the use of time series analysis to link demand with various occupant, building or weather related factors for more accurate predictions of peak demand. Examples include Bass's model [5] to simulate electrical demands for an individual consumer, aimed at sizing wind generators for remote island communities. The widely-used Tesla model was developed in conjunction with London

Electricity plc [6] and is claimed to be the most accurate currently available. Tesla adopts a variety of analytical methods to predict demand in terms of identifiable, latent, exceptional and unpredictable influences. The concepts have more recently been adapted to operate within a neural network model [7].

Models such as Tesla are extremely useful for predicting demand at the macro level – especially peak demands. Now that the collection and processing of large quantities of data is far easier, it is feasible to analyse electrical demand in more detail for a wide range of different consumers. The Load Research Group of the UK's Electricity Association is conducting such an investigation for both domestic and non-domestic consumers [8]. The results provide average daily demand on a half-hourly basis for different days of the week, seasons and categories of consumer. The work has been largely driven by trading requirements within the supply chain but is also used to support policy definition by the UK government for electrical demand reduction [9].

Bartels, whose research in Australia investigated demand on an end-use basis, recognises the importance of such models for policy making:

"They are the only demand-modelling tools capable of analysing the impact of technological change or policy initiatives with respect to particular end-uses. Any attempt to reduce carbon dioxide emissions by encouraging households to use less energy or switch fuel types will have a very different impact on different end uses"
[10, p.2]

Much of this previous work has either concentrated on predicting peak/average demand over a large group of consumers or on detailed estimation of demand for a single consumer. The SEnTIENT load models aim to provide a sufficiently detailed model at the individual level in order to provide a realistic picture of the minute-by-minute changes in demand within groups of consumers. The adoption of an end-use basis provides the network tool with the necessary estimates of active and reactive loading at each connection point.

4. SEnTIENT Load Model Concepts

Modules within the model predict demand for a variety of end-uses, dependent on the category of consumer: for example, for domestic consumers, these might include:

- Space heating
- Lighting
- Refrigeration
- Washing and cleaning
- Leisure (televisions, computers, videos, etc.)
- Water heating

The end-use sub-models are built using a generic methodology that can readily be extended to accommodate new types of end-use or modifications to existing sub-models (figure 4).

Since half-hourly averaging is frequently used in the electrical industry, the model adopts this as a first level basis for estimating demand. For domestic consumers, the model is based on measurements of end-use demand for nearly 100 homes, spread across the UK, provided by the Load Research Group of the Electricity Association. Demand variations during the day arise from a complicated mix of factors, including changes in daylight and temperature as well as patterns of occupant behaviour. The daily profiles of demand, as in figure 3, are relatively difficult to represent for each day of the year. For example (figure 5), the demand for domestic lighting during the morning peak is relatively constant, in terms of timing, throughout the year, regardless of the variations in sunrise. However, the evening demand is very dependent on available daylight and varies enormously over the year. There is clearly a complex interplay between components that relate to the sun and human behaviour that varies during the course of the day. To isolate this variation as far as possible it is convenient to analyse the trends in demand for each half-hour on an annual basis.

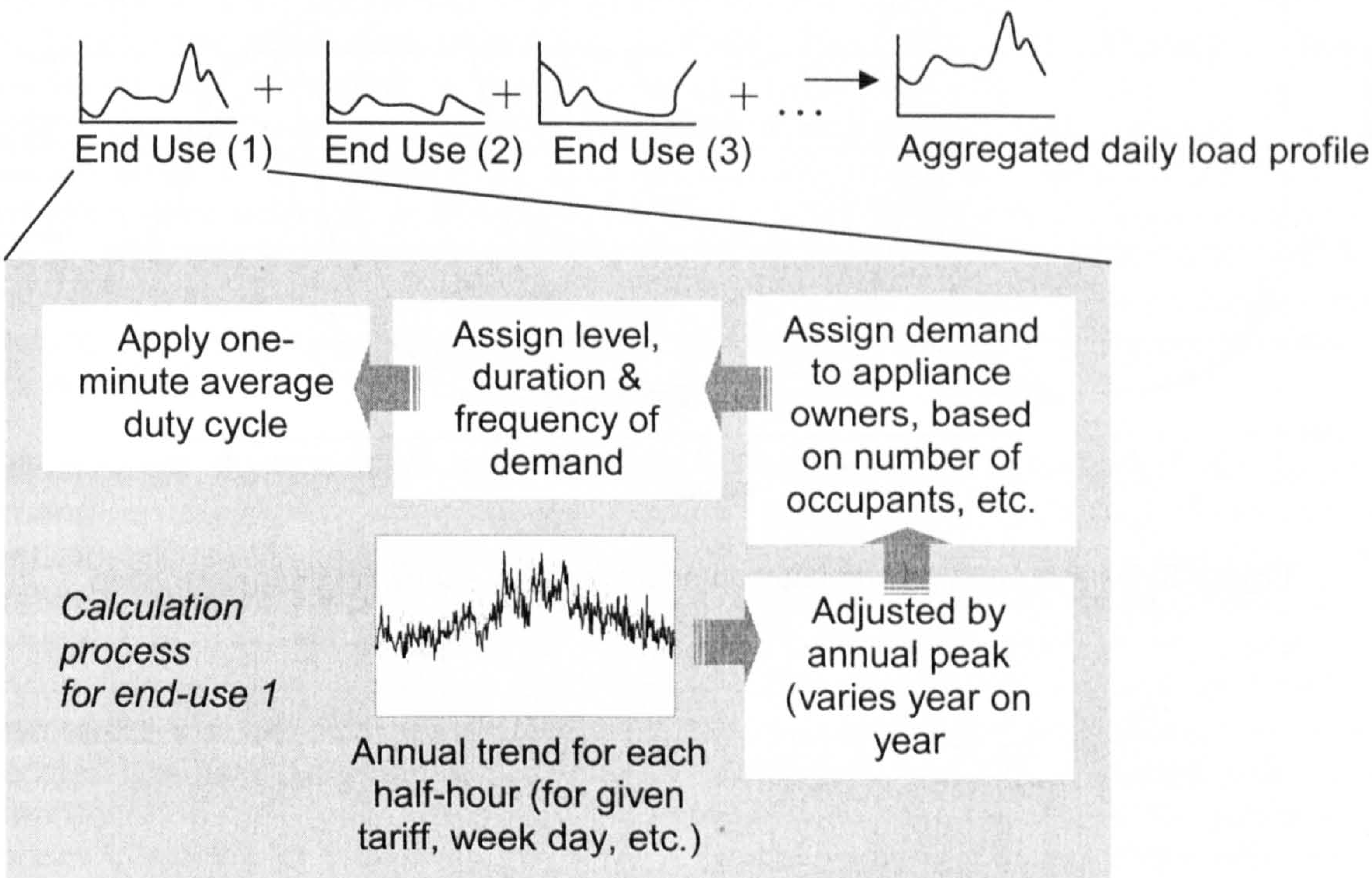

Figure 4: Conceptual basis for SEnTIENT load models

For a particular end-use, the annual trend is usually related to ambient temperature (or in the case of lighting, daylight variation), represented by a sinusoidal relationship. A normally distributed random element is added to the basic trend to represent the random variations in consumer behaviour and weather effects. The basic equation of the annual demand trend for a particular end-use sub-model is as follows:

$$D_{\text{end-use 1}} = s_{\text{end-use 1}} * \sin\{2\pi*(N_d/366) - \phi_{\text{end-use1}}\} + k_{\text{end-use1}} + r_{\text{end-use1}}$$

where:

$D_{\text{end-use 1}}$ = half-hourly average demand (usually scaled by the annual peak demand)
$s_{\text{end-use 1}}$ = sine scale variable
$\phi_{\text{end-use1}}$ = sine phase variable
$k_{\text{end-use1}}$ = sine function constant
$r_{\text{end-use1}}$ = random element of zero mean and given standard deviation, $sdev_{\text{end-use1}}$
N_d = day number (i.e. 1st January = 1)

Figure 6 demonstrates the relative accuracy of the half-hourly prediction – in this case for refrigeration demand between 18:00 and 18:30. It is usually necessary to model the half-hourly demand trends for different tariffs and days of the week.

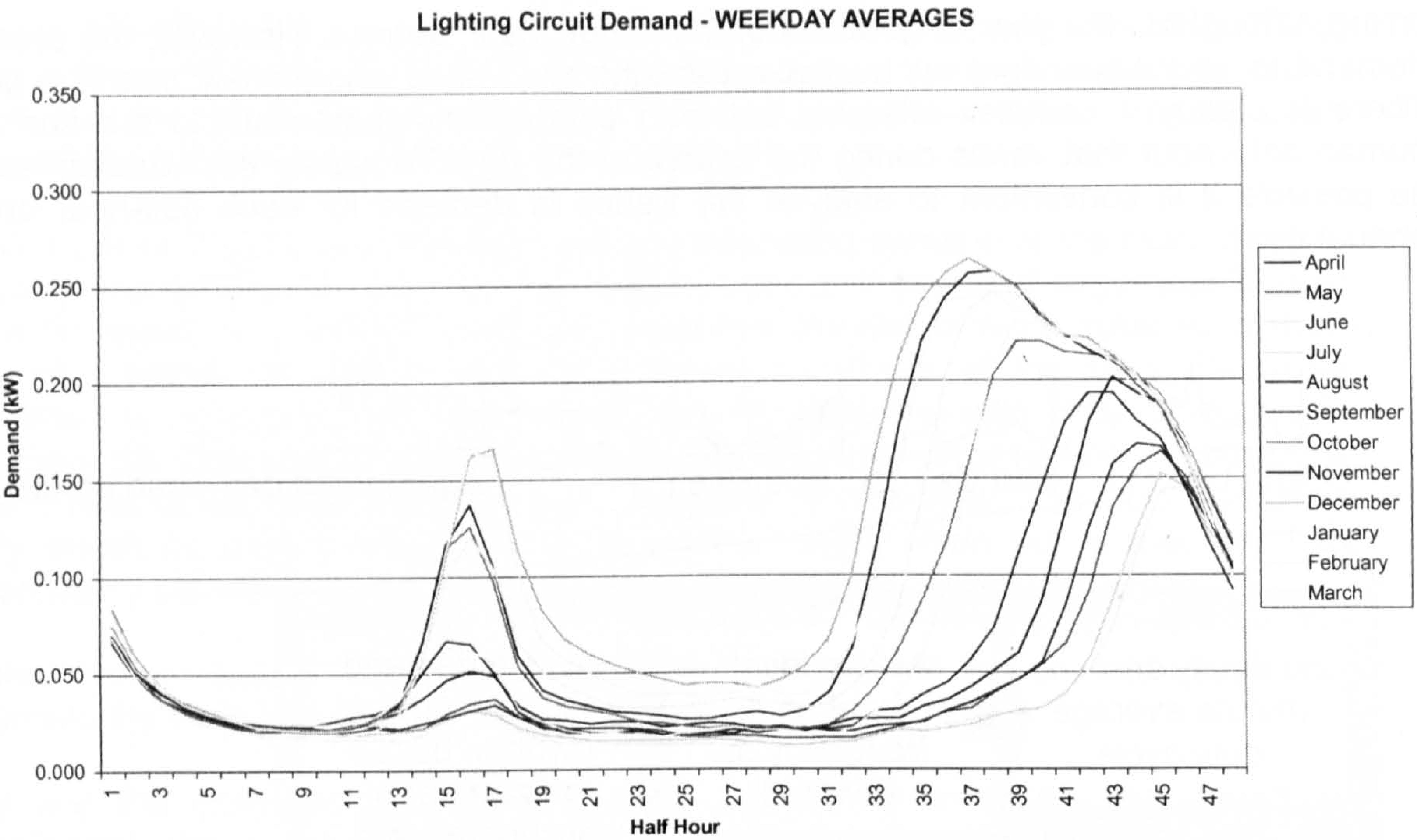

Figure 5: Daily profiles for weekday domestic lighting – showing annual variation

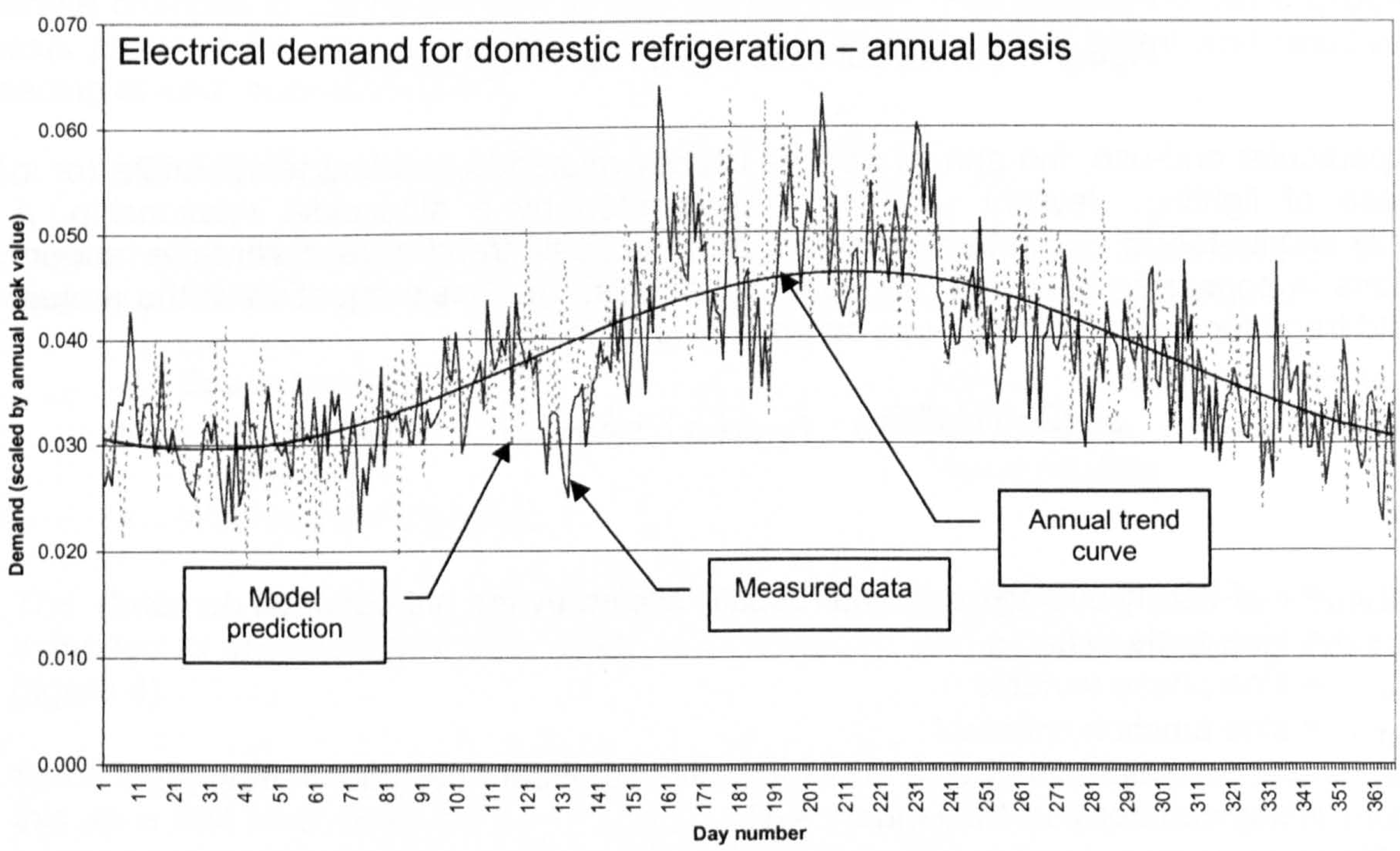

Figure 6: Comparison of model prediction with measured data for refrigeration demand (18:00-18:30)

At this stage, the model provides a simulation of demand trends for an average consumer. The trend is scaled by the estimated peak demand in any given year – thus year-on-year changes in use patterns and appliance efficiencies are taken into account. The next step involves allocation of demand to individual consumers. The first issue is ownership. Since data collection is expensive and time consuming, it is highly desirable to build models such that users may input data of varying accuracy depending on availability. The use of defaults in energy models is a well-practised technique [11]. For the SEnTIENT load models, the user may choose to input data at the national, urban, regional or individual level. In terms of existence of an end-use demand, national statistics may be used for ownership – for example, in England and Wales, around 43% of homes use a refrigerator (around 65% use a 'fridge-freezer'). The model also takes account of multiple ownership – (around 29% have both a refrigerator and a freezer). For a given group of consumers in a network, ownership of an electrical appliance is distributed randomly unless more specific data is available.

In most cases, the level of demand is related to the number of occupants and the average demand is scaled by an occupancy factor (the Building Research Establishment's standard occupancy calculation [12] is used, based on the ground floor area – one of a number of parameters available from the layered Ordnance Survey map using a toolset developed in a linked project [13]). Finally, a variety of duty cycles are triggered with varying frequency and duration that represent the one-minute average demands for a given appliance. Duration and frequency of the events are generally adjusted to match the allocated half-hourly demand and the level of demand is randomly assigned within a range – representing the variation in individual appliance efficiencies currently available. With random triggering of appliance demand, even consumers with the same allocated half-hourly demand will have differing one-minute demand profiles.

Each appliance or end-use demand is associated with a specific power factor (ratio of the active and reactive loads) and these factors are used when the various demands are aggregated to provide the total active and reactive power per consumer. These one-minute average values are fed into the load flow tool to simulate the loading over a chosen area of the LV network.

Clearly the model does not take account of all factors that affect diversity but a reasonably representative simulation is possible that includes diversity in ownership, scale of demand, appliance use patterns, efficiencies, duty cycle variations and general year-on-year trends. Whilst much of the preceding discussion relates to the domestic consumers (most of the work to date has concentrated on this sector) the use of a similar concept will be investigated for the non-domestic sector, especially for consumers with a peak demand below 100kW.

5. Case study

Once SEnTIENT has been prototyped to a satisfactory level of performance, it is proposed to conduct a sizeable case study in a central area of the city of Leicester, UK. Preliminary studies will involve running the load model with the aim of calibrating the system against known half-hourly aggregate loads metered at two selected primary substations. These will be chosen to achieve a representative mix of domestic and non-domestic consumers in the areas served. The three dimensional form of these areas will be modelled using an established CAD methodology based on recent photogrammetric data. Future scenarios will then be constructed in which the uptake of the solar technologies is envisioned on both a limited and a more intensive scale. The best available socio-economic and technical projections will be used to establish baselines for penetration at projected points in time. Using annualised ICUE [1] irradiation maps and SEnTIENT's customised graphical selection tools, likely sites will then be chosen for PV and solar thermal installations. The load model will then be exercised in conjunction with the solar energy models. For computational efficiency, short time-scale simulations using ICUE will provide a set of orientation-varying exemplars. Individual consumer locations and sets of locations aggregated on similarity measures will be matched to provide good estimates of supplied solar energy on the required time-scale. The time-varying loads, factoring in the solar contribution, will be calculated and made available to the load-flow analysis software. It will then be possible to interrogate the interactive LV network image in order to visualise effects (such as voltage increase or exceedance of thermal limits) on the electricity supply. Any potential problems will be identified and reports generated. These will form the basis for a discussion document - aimed at LA planners and DNOs - in which the implications of the preliminary findings, the potential of the tool and the indications for further study will be set out.

6 Conclusion

An accurate picture of the distribution of loading on the LV network requires realistic models. In particular, they are required to represent the diversity between consumers and the sharp fluctuations in demand – detail that is lost in the aggregated demand profiles at the primary sub-stations. Important techniques, previously adopted for load estimation, have been described, the particular advantages of end-user modelling have been identified and some of the many difficulties associated with accurately predicting the time-varying electrical demand of individual consumers have been discussed.

In this light, the end-use based SEnTIENT load model has been proposed as a means of producing the necessary accurate demand estimates for LV network simulation and design, based on the premise of increased penetration of solar and other renewable and novel energy technologies. Important features of the model that distinguish it for this role have been highlighted: the end-use basis, predictions for consumers using location-specific data, and the use of one-minute timescale. Additionally, the advantages of the proposed generic methodology for building end-use modules can be summarised. This will enable users to vary the basis of the model to reflect changes in technology and lifestyles. The ability to introduce social factors that affect ownership of appliances, level of demand and use-patterns, will give planners the opportunity to investigate a wide variety of scenarios. Variables such as the degree of uptake of renewable technologies, the age or employment profile, may be introduced to examine the effects on electrical energy demand and the associated carbon dioxide emissions. The SEnTIENT models should prove useful in devising and targeting solar energy strategies both for existing regions of cities and for new development planning.

Acknowledgements

This research is funded by the Engineering and Physical Sciences Research Council, project number GR/N35694/01. The authors are grateful to the Load Research Group of the Electricity Association for providing half-hourly demand data.

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SOLAR CITY : ASSESSING THE DETAILED EFFECT OF SOLAR TECHNOLOGIES ON ELECTRICITY NETWORK PERFORMANCE

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SUMMARY

Solar City is a project that aims to support designers of low voltage networks by modelling the effect of solar technologies used in urban areas. This paper describes the detailed load models, network analysis, software tool and test case that form the project output.

INTRODUCTION

Low voltage (LV) network designs based on heuristic approaches for estimating demand have so far worked well. As interest in renewable energy technologies increases, an understanding of the detailed impact of embedded generation on local demand and hence on LV networks becomes important. This in turn requires a better representation of the distributed load. Whilst considerable effort has been directed at modelling demand in the high and medium voltage areas of the distribution network, approaches to provide an accurate picture of distributed load within the LV networks are relatively sparse.

As well as a paucity of detailed load models there are few software tools available that support the design and development of the LV networks. The Solar City project aims to provide such support by linking fine-grained load models and a network analysis package within a software tool, SEnTIENT (Solar Energy Technology: Impact on Electricity Networks Tool). This paper describes the various elements of SEnTIENT in more detail but begins with a brief review of some of the modelling approaches that have been developed previously.

BACKGROUND

Most existing LV networks have been designed on the basis of empirical estimates of peak and average demands. Aggregated demands are calculated using a diversity factor. Research in New Zealand [1] revealed that there is a significant variation between the estimates used by different distribution network operators (DNOs) and generally such approaches can lead to over-engineered designs.

Another approach to estimate the scale or pattern of demand is time series analysis of measured data. For example, Bass [2] developed time series models to size wind generators for remote locations. The TESLA model [3] is widely used in the UK and adopts a time series approach, together with a variety of other analytical techniques, to estimate identifiable, latent, exceptional and unpredictable elements of the electrical demand. The Bass model provides half-hourly estimates suited to individual dwellings whilst the TESLA model is aimed at estimating peaks of aggregated demand over a supply region. Only a few modelling approaches, for example the work by Hyland and McQueen for domestic demand in New Zealand [1], provide continuous estimates of demand and account for diversity between connections. This is especially important to assess the detailed effect of solar technologies – identifying the duration and locations of voltage overloads in a local network clearly depend on it.

By adopting an end-use basis for demand models, such as for cooking, lighting, heating, cooling, etc., their application becomes more flexible. The models facilitate studies of changes in ownership, use patterns, efficiency and lifestyle – allowing demand patterns to remain realistic. In addition, relating components of the demand to particular appliance types allows a more accurate estimate of the active and reactive elements of the load. In the 1940s, Arvidson [4] examined a simple model that included nine different end-uses and provided a daily demand profile for each. Demand was derived from an hourly load that reflected occupancy behaviour and a basic profile that allowed for variation in the weather, built-form and building materials. Since then more complex models have become viable such as Bartel's work in Australia [5] and Capasso's research in Italy [6]. However, few models based on end-use are concerned with both demand and diversity.

The requirements for the Solar City load models are these:

- Load estimate per consumer connection point – for a realistic load distribution
- Coverage of both domestic and non-domestic (<100kW) demand
- End-use basis – to protect against future changes in demand patterns and to estimate power factors

- 1-minute average basis to capture spikes in the individual demand

Consequently, it was necessary to develop an alternative basis and methodology for the load models.

Sizing conductors in the LV networks has in the past, like load estimates, relied on considerable experience. Analysis tools that support network designs tended to specialise in primary distribution where decisions had far more impact on performance and capital cost. Tools for LV analysis must be suited to the multiplicity of nodes and radial nature of the network. Preliminary investigations under Solar City have shown that the Ladder Iterative Technique developed by Kersting is especially suited to this type of analysis [7]. A tool is being developed in MATLAB that performs an unbalanced three-phase power flow analysis. Early results on a 40-node network look promising.

A single feeder from a primary transformer can supply more than a thousand nodes and consequently some form of post-processing is required. Both the load models and the network analysis package for Solar City are linked by the SEnTIENT tool, which is described in the following section.

SEnTIENT – DESIGN CONCEPTS

The tool is based on dynamically linked relational database (MS Access) and Geographical Information System (GIS) technologies (MapInfo), allowing the LV network to be represented in a highly maintainable and user friendly way. Computationally intensive aspects of the work such as the demand and solar energy models are being implemented as object-oriented dynamic link libraries (DLLs) that can be called from both the database and GIS applications. The user may query both network detailed design (line lengths, conductor types, etc.) and performance (over-voltage, over-heating, etc.) directly from the GIS.

The advantages of linking relational databases dynamically with a GIS are numerous. In this context, the user will be able to select a connection point in the library whilst simultaneously viewing the location on the map. Similarly the detailed demand profile for any connection point can be viewed in both ways. The tool will allow the user to adjust the underlying load model to simulate changes in the assumed profile of the network area to reflect different lifestyles or energy saving strategies.

The basic function of the GIS interface is to pull together the various strands of the package (figure 1), linking the various libraries, load model, network analysis package and an element known as ICUE [8], which estimates the solar yield from photo-voltaic (PV) or solar-thermal panels. ICUE facilitates the selection of appropriate sites for solar panels. This irradiation-mapping tool uses a 3D model of

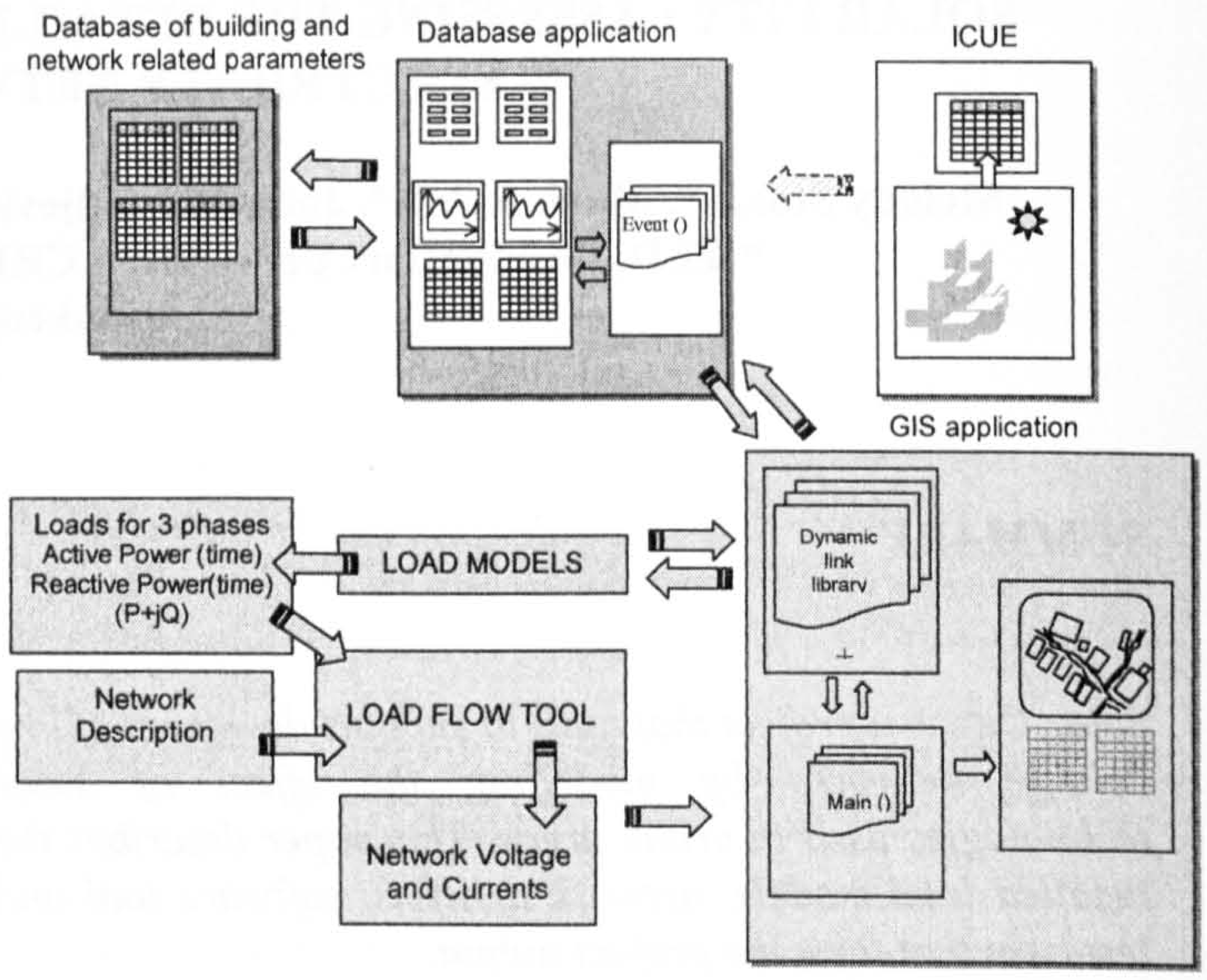

Figure 1:Block diagram showing the concept design of the SEnTIENT tool

the network area, based on photogrammetry. The solar yield is estimated for both direct and diffuse radiation and produces a false-coloured contour image. This enables the user to define panel sizes to suit the location and to maximize the output. The estimated irradiation value for a panel is then used to predict the extent of exported supply (PV) or reduction in the modelled demand (solar thermal).

The network design can be readily modified and reports obtained on the associated performance factors such as peak and average voltages or duration of over-voltage. The tool will also highlight the location of problem areas in the network. Such features allow the user to quickly compare different design options in order to establish the best compromise.

SEnTIENT LOAD MODEL

All the end-use sub-models of the SEnTIENT load model are based on the same underlying methodology (figure 2).

The demand for domestic consumers is based on half-hourly averaged data. The daily profile for demand is highly non-linear due to the effects of occupant behaviour and the changes in the availability of solar heating and lighting. During the course of the day, demand varies due to the complex interplay of these factors.

For example (figure 3) a typical weekday profile for a domestic consumer shows low demand during the night with two peaks representing the demand at breakfast and during the evening. Demand during the day tends to be low because dwellings may be unoccupied and also because natural heat and light are available.

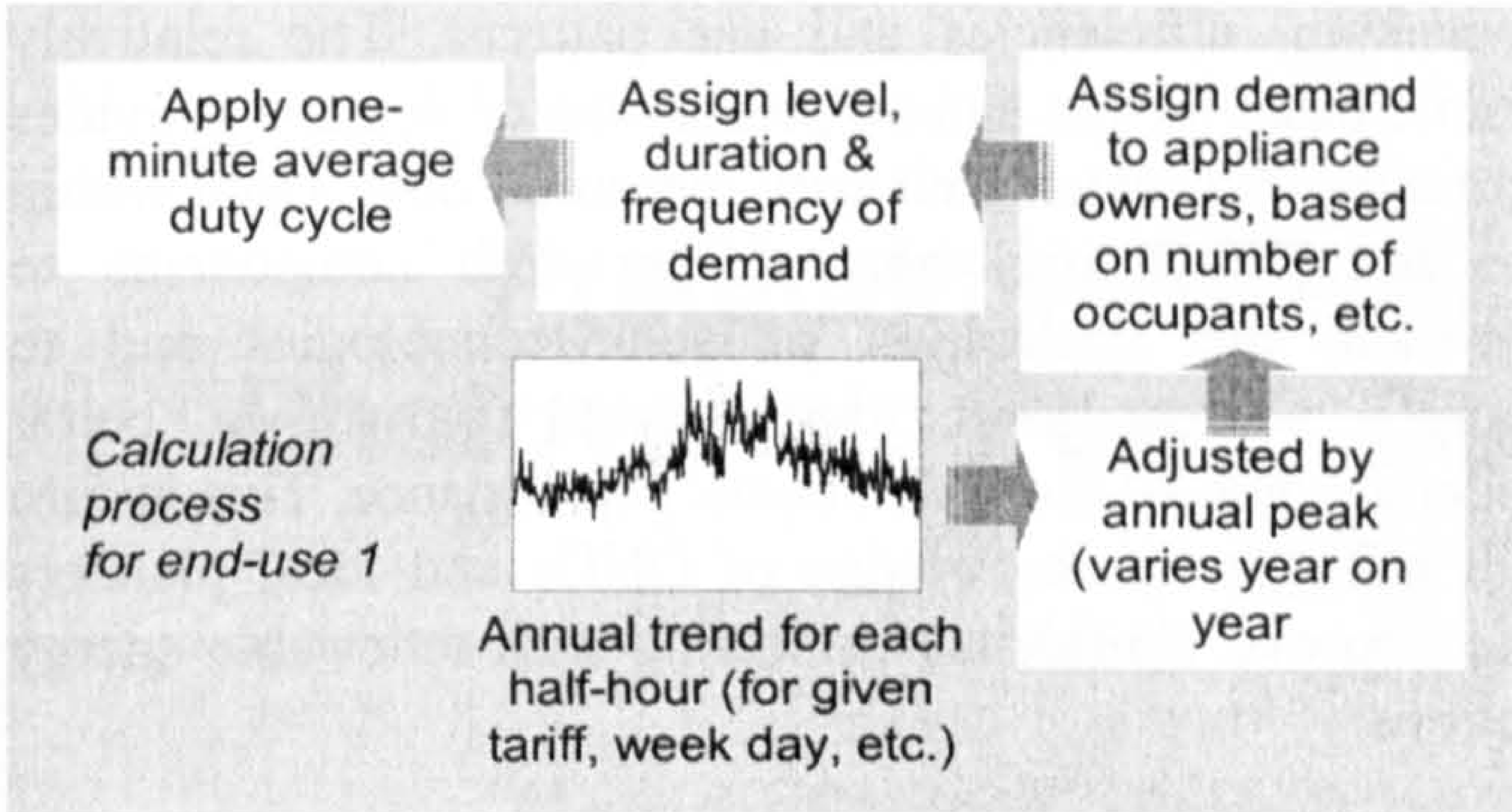

Figure 2: Conceptual basis for the SEnTIENT load models

By analysing the annual instead of daily trends in demand, the variations due to occupant behaviour are reduced, especially if demand is analysed separately for different day types (weekdays, Saturdays, Sundays with special cases for public holidays). For the end-use demand, the annual trends can generally be expressed as the combination of a basic sinusoidal component, that represents the effect of solar heating or lighting, and a random element, that represents the variation in occupant behaviour and weather effects:

$$D_{\text{end-use 1}} = s_{\text{end-use 1}} * \sin\{2\pi*(N_d/366) - \phi_{\text{end-use1}}\} + k_{\text{end-use1}} + r_{\text{end-use1}}$$

where:

$D_{\text{end-use 1}}$ = half-hourly average demand (usually scaled by the annual peak demand)
$s_{\text{end-use 1}}$ = sine scale variable
$\phi_{\text{end-use1}}$ = sine phase variable
$k_{\text{end-use1}}$ = sine function constant
$r_{\text{end-use1}}$ = random element of zero mean and given standard deviation, $sdev_{\text{end-use1}}$
N_d = day number (i.e. 1st January = 1)

To model lighting demand, it is necessary to use two sinusoidal components of different phase and amplitude. For many end-use demands there tends to be minimum and maximum cut-off levels to the demand in summer and winter.

The half-hourly demand is divided by the annual peak, such that the model provides non-dimensional trends that may be scaled to reflect year-on-year changes. The match between the modelled demand and measured data is generally good (figure 4, lighting demand for a typical domestic consumer, between 19.30 and 20.00 on a weekday)

Existence of a demand at an individual node is determined by assigning ownership of a particular end-use or appliance. By default, national average data is used. The SEnTIENT tool will allow users to input data at national, regional, local or consumer levels, depending on the availability of data. This feature allows users to balance the accuracy of the demand predictions against the cost of gathering data.

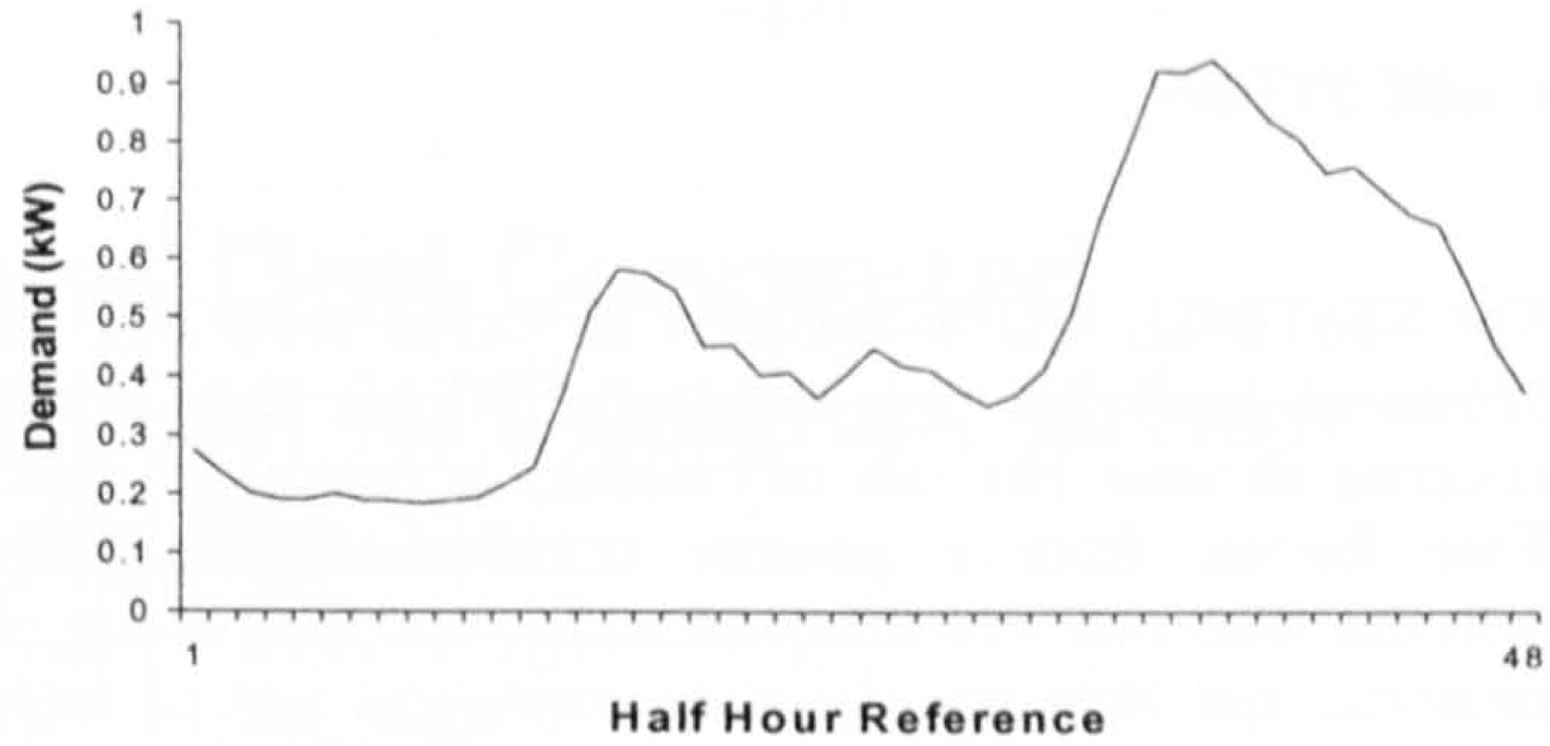

Figure 3: Typical half-hourly domestic daily demand profile

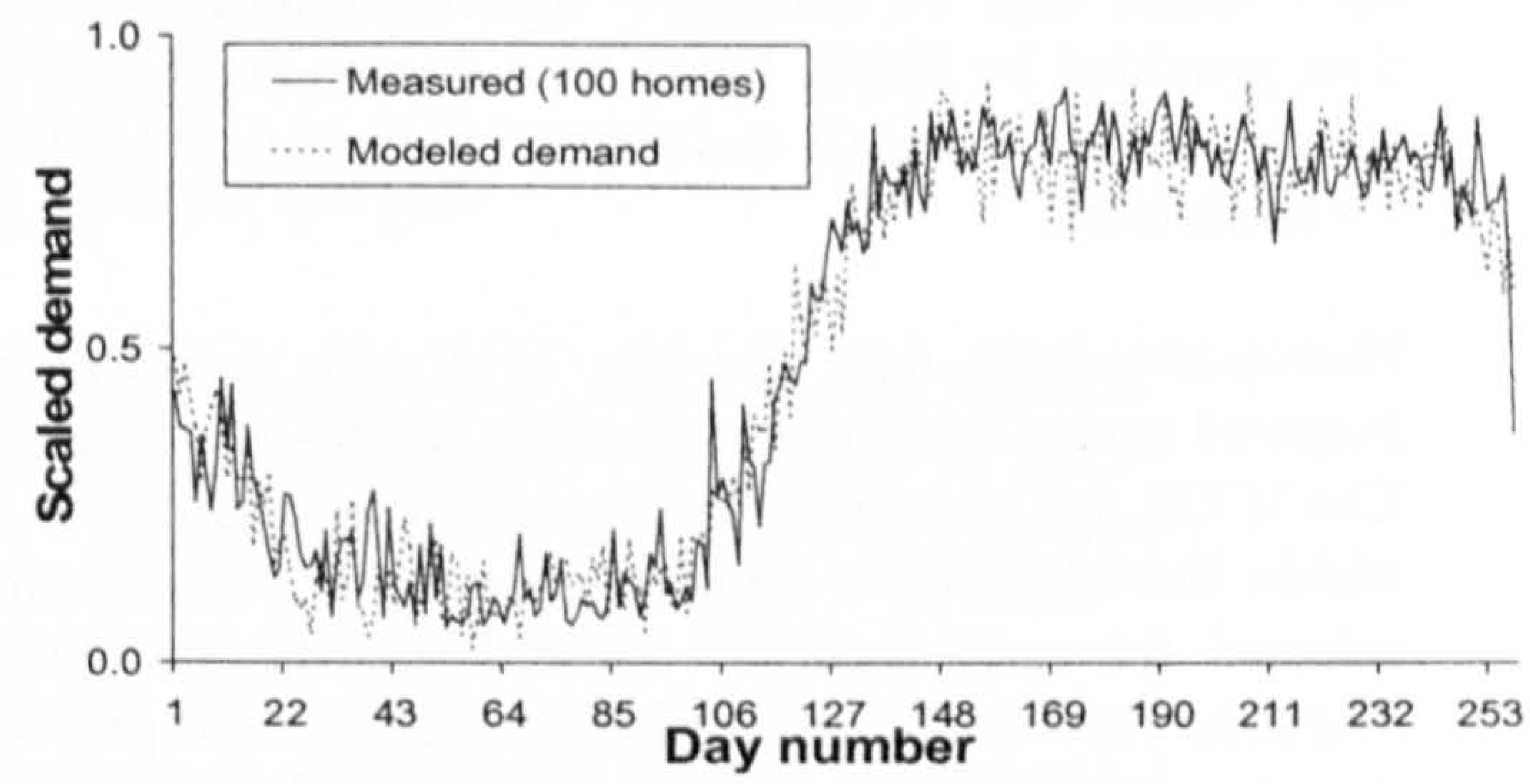

Figure 4: Comparison of modelled and measured lighting demand for a typical domestic consumer (annual trend for weekdays, between 19.30-20.00)

For consumers with assigned ownership, the average half-hourly demand is scaled by a relevant factor, such as floor area or occupancy, to introduce a further realistic element of diversity. An appropriate appliance duty cycle is triggered randomly to provide 1-minute average demand such that the total in each half-hour is matched to the assigned value. The duration, frequency and scale of an individual demand event are varied randomly within specified bands. This provides a further element of diversity such that consumers who are assigned identical half-hourly demand will appear to have different 1-minute average demand profiles. For each end-use, the output will be 1-minute average demands with an associated power factor. By combining the various end-use demands, the total active and reactive components may be calculated for each individual node of the network.

The model is intended to include light non-domestic consumers, with a peak demand of less than 100 kW. Consumers above this limit tend to use half-hourly metering. The non-domestic model will be based on similar annual trends for end-use half-hourly demand but each half-hour will be scaled to suit the business activity – to reflect the different daily profile of demand that will arise. The ICUE tool will provide an estimated yield from solar-thermal or PV panels associated with a given node. The estimated output will then be used either to modify the modelled water heating demand or to reduce the total demand.

CASE STUDY

The SEnTINEL tool is designed for urban areas and for validation purposes, a case study will be conducted, covering an inner city area of Leicester in central England. Two feeders from a primary transformer have been selected, with over two thousand nodes, including a mix of domestic and light non-domestic consumers and of built forms, to test the irradiation aspects of the tool. Nodes have been identified from maps provided by Leicester City Council and network data from East Midlands Electricity (EME). The total demand estimated by the load model for each feeder will be compared with half-hourly measured data provided by EME, for at least one annual cycle. The match between the scale and pattern of demand will be used for calibration.

Photogrammetric data for the area has recently been acquired and is being used to build a 3D model using CAD. The ICUE model will provide annual irradiation maps and within the SEnTIENT interface, appropriate sites will be selected for assignment of PV and solar-thermal panels. The load models and irradiation predictions will provide a time-varying pattern of distributed demand over the network area. The results will be fed into the network analysis tool to perform the unbalanced three-phase power flow investigation. The GIS interface may be used to visualise the effects and areas of concern within the network supply. Reports can then be generated which examine the statistics of performance.

The prime motivation for the Solar City project is to examine in detail, the effects of different levels of uptake of solar technologies. The results are intended to provide guidelines to DNOs and urban planners. Such issues as the effect of the density of solar technologies, targeting certain types of consumer for peak reduction or design rules for connection to the LV network are likely to feature in the planned dissemination. However, the tool should provide a useful basis for wide-ranging investigations of electrical energy demand issues.

CONCLUSION

A detailed understanding of the distributed load is required to assess the potential effect of solar-technologies on LV networks. Few load models provide sufficient information to describe the high degree of diversity between consumers and the time-varying nature of the individual demand. Whilst a number of different approaches already exist the requirements of the study have led to the development of a unique, fine-grained load model.

The SEnTIENT load model aims to provide a realistic picture of demand, representing the diversity arising from ownership, efficiencies and use patterns. The relatively simple basis for the annual predictions of demand provides estimates that match well with measured data. Used within the SEnTIENT package, together with components to represent the application of solar-technologies and to analyse power flows, they should provide a better understanding of the LV network performance. This in turn will enhance the knowledge of DNOs and local planners and improve confidence in dealing with renewable energy options.

ACKNOWLEDGEMENTS

This research is funded by the Engineering and Physical Sciences Research Council, project number GR/N35694/01. The authors are grateful to the Load Research Group of the Electricity Association for providing half-hourly demand data and Leicester City Council for supplying maps and address point data for the test case.

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Paper Code –UK24

Predicting the Effects of Grid-Connected Photovoltaic Power Generation in Complex Urban Environments

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ABSTRACT: This paper describes the development of a tool to support investigation into the possible effects on electricity supply networks of urban grid-connected photovoltaic (PV) schemes. The Solar Energy Technology: Impact on Electricity Networks Tool (SEnTIENT) is based on a Geographical Information System (GIS) and will enable the prediction of local low voltage electricity network performance at a relatively early planning stage. It will incorporate advanced load-flow analysis techniques, realistic object-oriented domestic and non-domestic consumer load models, and electricity network mapping algorithms. A technique known as Irradiation Modelling for Complex Urban Environments (ICUE) will support rapid solar panel site selection with optimisation for delivered energy replacement and CO_2 mitigation. The need for the tool is explained, the design of the software is described and a methodology for deploying the tool to scenarios of interest is proposed.

Conference Topic: Methods and Tools for Design Assistance
Keywords: energy modelling, electricity demand, network, photovoltaic

1. INTRODUCTION

Governments across the world are investing in policies that encourage and support the use of renewable energy sources (RES). In the urban environment, solar photovoltaic (PV) and solar thermal technologies are likely to become increasingly important. Replacement of delivered energy on a large scale by grid-connected PV in particular may have a significant impact on low-voltage networks. Even if overall levels of penetration do not increase dramatically, urban planners, responding to policy at national level, may choose to select specific communities for the introduction of RES. These local concentrations are equally likely to have implications for network operators, as it is at this level in the network that the effects are likely to be most noticeable. It is therefore essential to be able to predict the effect on the existing infrastructure and to support design decisions for the development of the local electricity networks. Simulations of proposed schemes will allow designers and planners to assess the risk with greater confidence. For the longer-term, new developments may be planned with sufficient potential for a wider uptake of solar technologies in the future.

In the UK, diverse stakeholders have interests in urban planning decisions that take electricity demand and supply considerations into account. The distribution network operators have a technical and financial responsibility for the quality of supply, while local authorities have a duty to monitor and help reduce energy demand within their area of jurisdiction. The UK government-funded project, Solar City, aims to provide the tools necessary to model solar energy technologies and to visualise effects on an urban scale, bringing together information associated with both electricity consumers and electricity network components.

The Solar Energy Technology: Impact on Electricity Networks Tool (SEnTIENT) incorporates a number of novel elements that are currently being developed and refined. These include a load modelling approach that provides a realistic load distribution over the network, a component for predicting the solar irradiation and investigating the associated yields and a load flow analysis tool that identifies power quality issues and highlights localised problem areas. These components are linked to a Geographical Information System (GIS) that provides a user interface for interaction with the consumer descriptions, their estimated demands and the details of the network and associated performance. This unique integration of support for key decision areas in RES planning will provide the means for early assessment of the associated risks as well as a platform for investigating different planning scenarios.

On completion of the tool, the results will be compared with measured electricity demand data, aggregated at the level of a single feeder on a primary transformer (supplying several thousand individual consumers). Experience with the test case is expected to provide a vehicle to generate detailed design guidelines for incorporation of urban RES.

This paper describes the various elements of SEnTIENT including an outline of the software design and a means of supporting the rapid site selection of solar panels. A methodology is proposed for the application of the tool during the planning process.

2. SEnTIENT – SOFTWARE DESIGN AND COMPONENTS

2.1 Basic Design

The GIS interface of SEnTIENT will allow the user to visualise the components of the local electricity network, including connecting lines and nodes, switching points and transformers. The interface provides access to detailed information on each of these components held within a dynamically linked database. Similarly, the address point locations and building outlines associated with each consumer connection will be visualised on the GIS and provide access to detailed information concerning assigned attributes of the consumers, such as category (domestic or business activity for non-domestic consumers), floor area, occupancy or lifestyle indices. Such information is used within the detailed load model to estimate the electricity demand.

The dynamic link between the interface and the database application allows switching between different views of the underlying data. For example, records associated with a consumer location (Address Point) or a network node can be accessed through the forms-based user interface in the database whilst the digital map will centre on the corresponding geographical location in the GIS. The GIS application also provides a link between the various elements of the software package (Figure 1):

2.2 Load Models

For the purposes of current network design, loading is frequently applied using values for the average and maximum annual demand and a diversity factor, based on the number of consumers connected, that allows for the variations in the individual demands (peak demand rarely occurs at exactly the same time for every consumer).

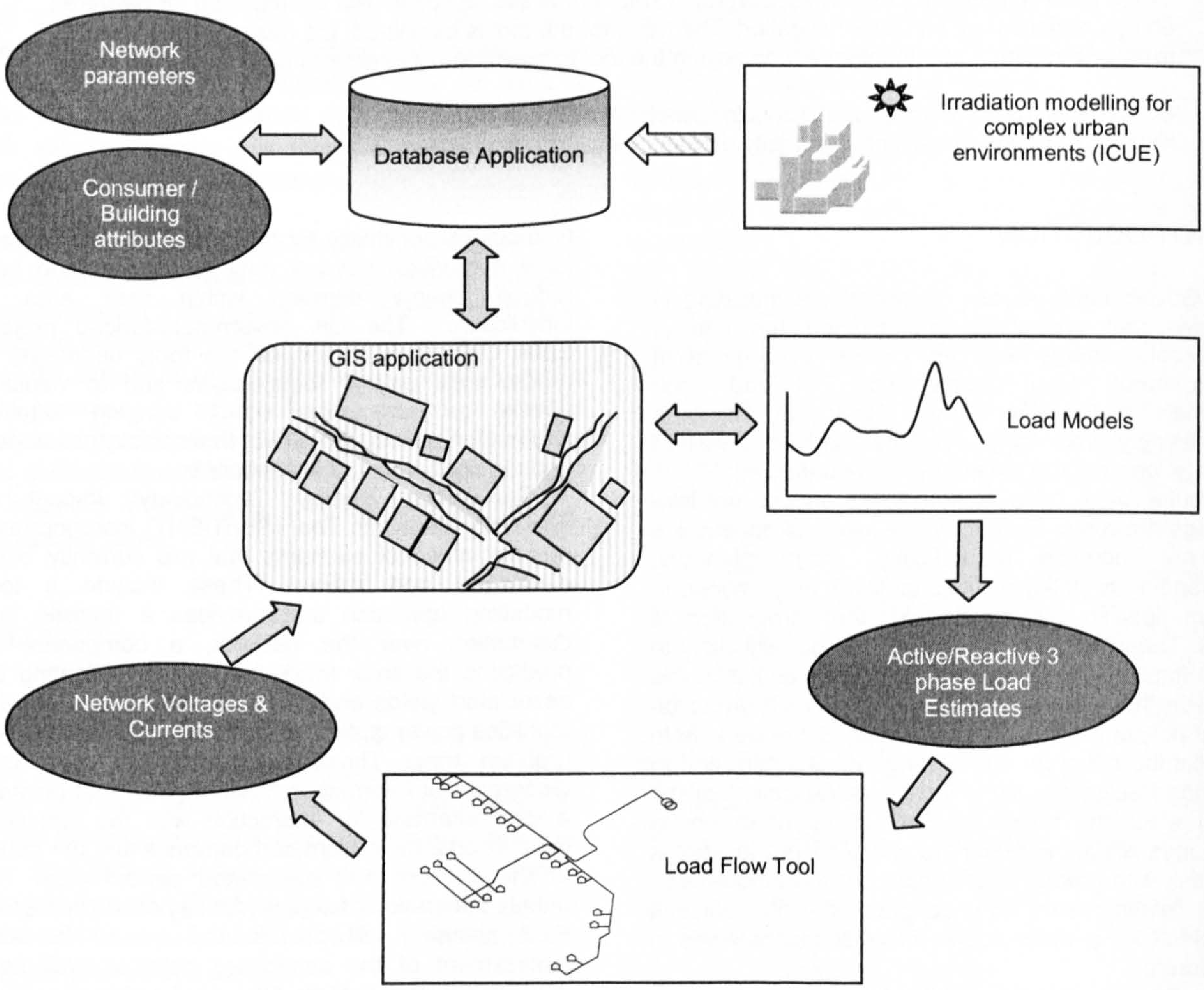

Figure 1: System design block diagram of the SEnTIENT tool

For sophisticated studies, a more accurate picture is obtained by assigning standardised profiles to different types of consumer - domestic consumers, depending on the tariff used or fuel used for heating, non-domestic consumers depending on the business activity. These profiles may be varied for different days of the week.

SEnTIENT however requires a more detailed description of the load, both in terms of diversity and temporal variation, in order to allow for examination of the localised effects of embedded RES generation and to compare supply and demand, taking account of the fluctuations in sunlight availability. These requirements present a considerable challenge. Load profiling and demand modelling tend to be based on half-hourly averaged data. Most of the modelling research to date has been aimed at the high to medium voltage networks, which have a much smoother profile since spikes in demand are eliminated in the aggregated data due to diversity. Consequently aggregated demand is much easier to predict.

Energy demand arises from a complicated mix of elements, including natural factors, such as ambient temperature and availability of sunlight, as well as the characteristics of the consumers, such as their lifestyle, income and the levels of occupancy. This leads to a mix of relatively predictable levels of demand together with a more random element.

In the past a variety of techniques have been adopted to cope with the random elements in the individual demand and that due to diversity between consumers. Time series analysis was used to provide simulated data for matching supply and demand for wind-generation on remote islands [1] but this was only for a single dwelling. Fourier analysis was used to model total demand as well as the diversity in the demand for a group of dwellings in New Zealand [2] but this required the use of a large number of individual demand profiles that are not readily available in the UK. Both these techniques are essentially 'black-box' solutions and do not provide bases that are readily understandable in a real-life context. Other researchers have attempted to model demand by separating the effects of the various influences – in one case [3], using an availability function to model when a building was occupied, a proclivity function to model when certain activities were likely to take place and end-use models to describe the likely demand from appliances. Such approaches are very useful but require sets of social data to describe the behaviour of consumers and businesses, which are often even harder to obtain than demand data.

Consequently a unique set of electrical load models (Figure 2) has been developed that allow a load profile to be described at each network connection point and on a time-interval upwards of 1-minute averaged demand. The models cover both domestic and non-domestic consumers and adopt a basis that can be associated with real-life factors that influence demand. By describing the consumers, end-uses and appliances as objects and identifying the associations between them, the model is relatively flexible and easy to adjust.

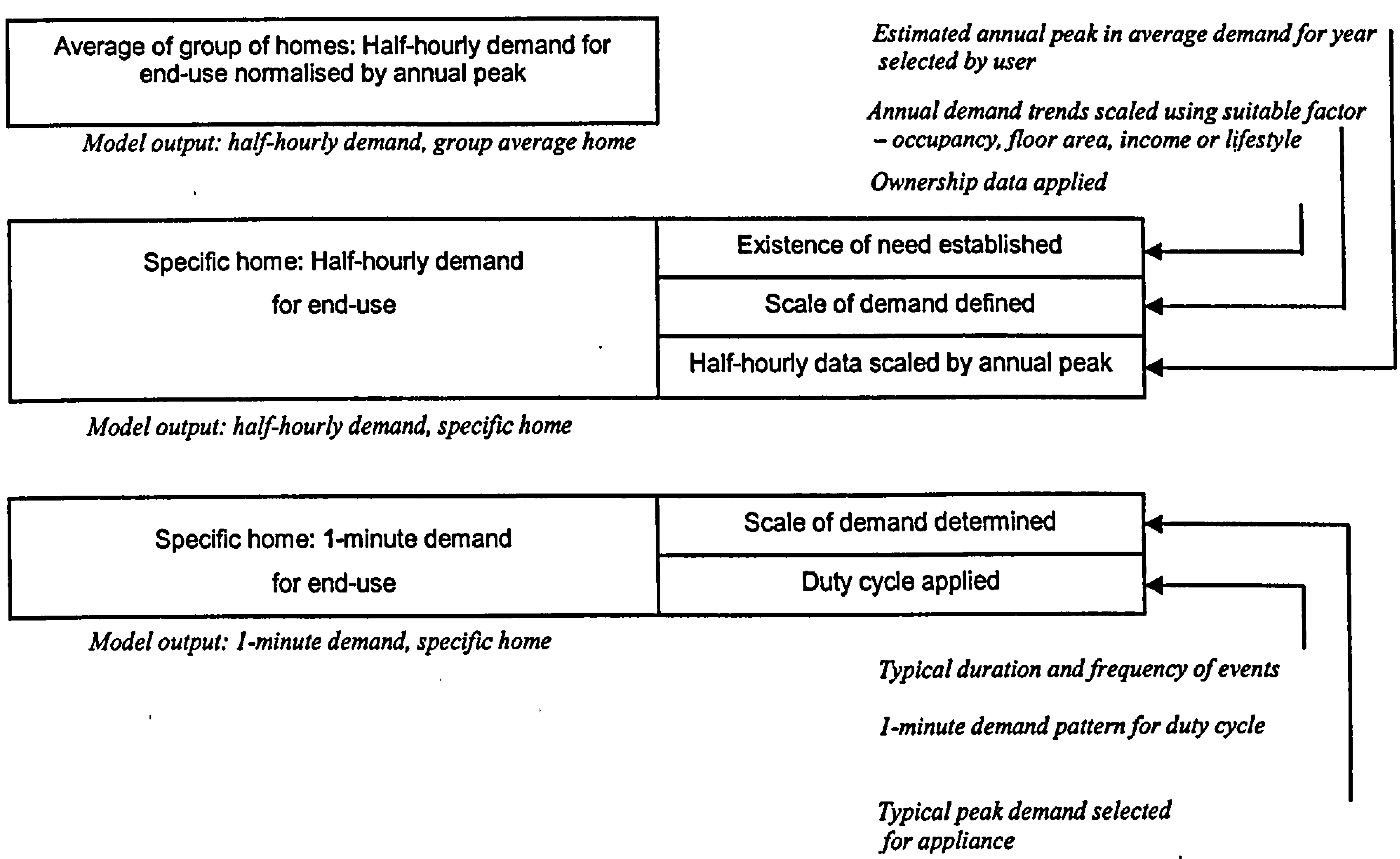

Figure 2: Conceptual basis of SEnTIENT load models

The electricity demands of each consumer are represented on an end-use basis, including components for lighting, heating, cooking, etc., which are aggregated to describe the total demand over the time period chosen by the user. The model is initially based on half-hourly demands, (taken from the average of measured data for a group of one hundred UK homes). The demand is normalised by dividing by the annual peak demand – this allows the user to incorporate long-term trends in the demand within each end-use and thus account for changes in the relative mix associated with different appliances. For example, in future the model may need to reflect growth in lighting demand as the number of luminaries per room increases but a reduction in cooling demand as refrigeration appliances become more efficient. The model is built in a flexible way such that the user may incorporate new end-use modules in the future. A stochastic element in the model allows for day-to-day random variations in demand that arise from changes in weather patterns or occupant behaviour (this is also based on measured data).

Diversity is introduced in several ways. Ownership assignment defines whether a particular end-use exists at a given connection point – statistical levels of ownership are used to make random assignments over the network area, based on available national, regional, local or specific data. If the need for a given end-use has been assigned, the half-hourly demand pattern is scaled by a suitable parameter that relates to the consumer. For example, cooking demand is associated with the number of occupants in a house and this in turn can be related to the floor area. The latter is automatically derived from the GIS using a novel foot-print tool that identifies the enclosed area from a building perimeter [4].

Each connection point is therefore assigned a pattern of half-hourly demand that is specific. The half-hourly assignments are used to estimate the demands averaged over a one-minute interval, based on the typical duty cycles or use-patterns for associated appliances. These 'use events' are set to occur with random start-time and duration and can be randomly scaled within a range, to represent the variation of appliance ratings currently on the market. The one-minute demand levels are matched to the assigned half-hourly demand. For example, for washing demands, the model stores a library of duty cycles that relate to different wash temperatures. The wash cycles are randomly selected and are triggered when sufficient half-hourly demand has been assigned. Thus, each connection point will have a unique demand profile that reflects the diversity observed in real life.

The preceding description concerns the domestic model. SEnTIENT is also applicable to areas where there is mixed use and covers non-domestic consumers. The non-domestic model uses a similar half-hourly basis as the domestic model, on the assumption that the effects of annual variations in the ambient temperature and daylight availability will be similar for all consumers. Adjustments are made to the daily profiles such that demand is increased during periods when business activity is high.

2.3 Load Flow Analysis

The load flow analysis provides data concerning the voltage and currents at each point in the low voltage network, revealing possible areas of over-heating. For SEnTIENT, an analysis package is being developed [5] that investigates all three phases of the low voltage network and uses a snap-shot analysis of the network performance taking the load distribution from the demand models. Such analysis for high and medium voltage networks is quite common although few attempts have been made to apply the techniques at the low voltage end of the distribution, which has a more complicated network design with a high density of connection nodes and a greater variation in demand.

SEnTIENT will provide users with reports of the network performance such as peak and average voltages and durations for out-of-limit operation. The GIS will provide the user with a basis to visualise problem areas and to make adjustments to the detailed network design.

3. ICUE APPROACH

The irradiation-mapping tool ICUE [6] provides a visual basis for the rapid selection of appropriate sites for solar panels. For the SEnTIENT application a scrollable false colour image will be generated from the large files of per-pixel irradiation values aggregated over a year, which the ICUE process creates. Users will be able to select the most suitable sites, sizing the panels to suit the location. In Figure 3, the plan view of a part of De Montfort University city campus is shown with the optional edge-extraction facility switched on. The solar energy supplied can then be accurately predicted for individual buildings or, to achieve computational efficiency in the case of numerous domestic buildings, for exemplars with a limited range of orientations with which similar types can be matched. In either case, the plan views of chosen buildings are linked back to footprints associated with footprints on the digital map. The solar energy supplied to each building can then be predicted over the timescale selected by the user, and output to the solar thermal and PV models. SEnTIENT will then predict the associated electrical generation or modification of water heating demand associated with each panel.

4. POTENTIAL APPLICATIONS OF SEnTIENT

When SEnTIENT is complete and satisfactorily validated, it will be applied to a test case area of Leicester, UK city centre. This area includes a number of high-rise buildings and a mix of domestic and non-domestic consumers on a single feeder from a primary distribution transformer. Photogrammetric data is being used to construct the three-dimensional city model, from which the user will define the location and size of solar panels, based on different scenarios of uptake.

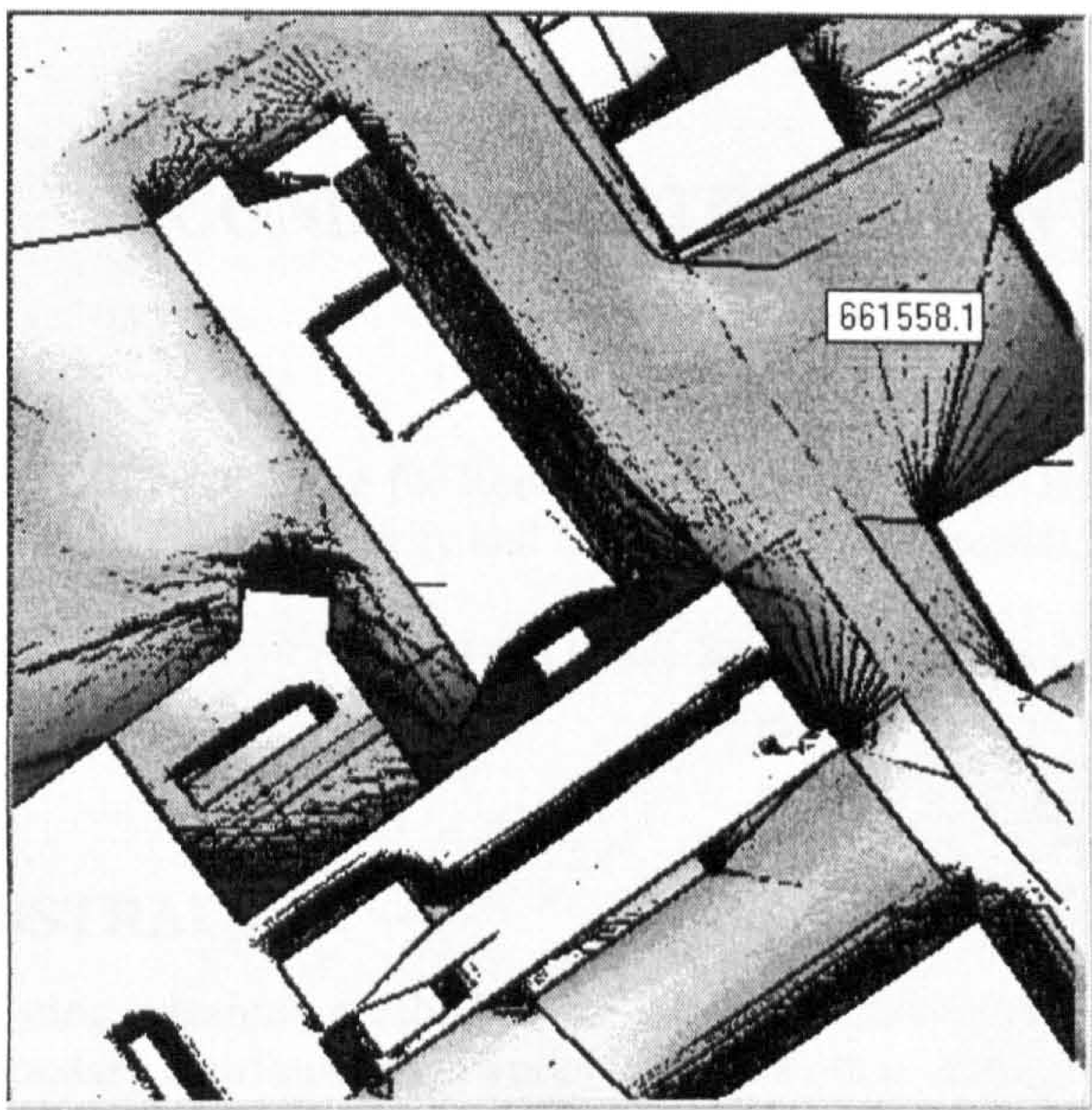

Figure 3: Example of ICUE plan view (edges extracted)

Address Point data has been gathered from local authority records. These are further sorted to define domestic and non-domestic consumers to whom ownership of end-use and scale factors for each of the end-use demands can be associated. Users will specify the time span of interest that SEnTIENT requires for calculation of the one-minute averaged demand patterns, aggregated from the individual end-uses and modified according to the yield from solar thermal panels.

The load distributions and their time-varying pattern will be applied to the load flow analysis tool, which will calculate the corresponding voltages and currents that occur on the feeder. The results of the load flow analysis will be visualised in the GIS, illustrating the locations of over-voltages or exceedance of thermal limits.

The tool will facilitate the simulation of a number of different scenarios and is expected to assist with both the planning process of local authorities and the detailed design of low voltage networks. SEnTIENT is also expected to provide the facility to investigate changes in energy demand that might arise from variations in lifestyle or appliance use, with the possibility to simulate different energy saving policies for the local area. SEnTIENT's design allows for application to a single dwelling, where a more specific picture of demand may be developed, through to large groups of consumers within a network area.

5. CONCLUSION

Widescale use or densely applied solar technologies in urban environments will inevitably have an impact on the local electricity networks. In order to assess the risks involved, simulation of these effects is an important feature of the planning process. SEnTIENT will bring together in a single environment a variety of elements that are aimed at supporting both planners and network operators.

A number of novel features have been described including fine-grained models that provide a representative load distribution on the network for both domestic and non-domestic consumers. These are based on end-use and include realistic descriptions of diversity between consumers, including lifestyle, income and occupancy for domestic consumers and business activity for non-domestic consumers. These load models will simulate the rapid changes in demand at each connection point that are important when comparing demand against supply from RES.

The load models will be used in conjunction with a network performance tool, the details of which have been outlined. SEnTIENT provides a useful interface for viewing problem areas and for making design adjustments.

The ICUE package will allow users within the GIS environment to site and size solar panels. The application of ICUE within SEnTIENT has been reviewed and the mechanism for estimating solar yield has been described.

When completed, the tool will support planning and design decisions and is expected to be of wider value in reducing energy demand and identifying target locations for solar technology deployment.

ACKNOWLEDGEMENTS

This research is funded by the Engineering and Physical Sciences Research Council, project number GR/N35694/01. The authors are grateful to the Load *Research Group of the Electricity Association for* providing half-hourly demand data.

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SECONDARY DISTRIBUTION NETWORK POWER-FLOW ANALYSIS

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ABSTRACT

Existing design methods for sizing conductors in secondary distribution networks (LV networks – typically below 500V) often employ Diversity Factors and rely heavily on a wealth of experience with similar networks and similar loads. The introduction of photovoltaic (PV) systems and micro co-generation (domestic combined heat and power: DCHP) will inevitably alter power flows in these networks, but since, at present, these distributed generators are few and far between, there is little data or experience on which to predict any effects they may have when widely installed. This paper describes on-going development of thorough and detailed modelling techniques, applicable to secondary distribution networks, using 1-minute time-series data and accurate unbalanced power-flow analysis (load-flow). These modelling techniques will provide a sound basis for the consideration of micro distributed generators.

KEY WORDS

Distributed Generation, Micro-Generators, Photovoltaics, Network Analysis

1. INTRODUCTION

Distributed generators alter the power flows in distribution networks. This can lead to localised over-voltages or exceedance of thermal limits, and these factors can present an upper limit to the allowable installation of generators in an existing network. Indeed, the risk of over-voltage is often the limiting factor for the connection of wind-turbine generators to primary distribution networks (typically 10–20kV), and the cost of reinforcing the network can be substantial.

Installation of photovoltaic (PV) systems and micro co-generation (domestic combined heat and power: DCHP) could face similar limits regarding connection to existing secondary distribution networks (LV networks – typically below 500V). Furthermore, increased use of solar water heating and improved architecture could dramatically reduce electricity consumption for heating and cooling, which would also alter network power flows. The authors are currently developing simulation software to investigate and quantify the potential effects of solar energy technologies and DCHP on existing distribution networks. The project is divided into two areas: load/generation modelling and network analysis.

Load models are very well established for the purposes of predicating bulk generation requirements and bulk power flows. However, these models are designed to predict the aggregated loads of large numbers of customers, and do not, therefore, represent the highly stochastic nature of individual customer loads. Such models are of limited value in modelling power-flows in secondary-distribution networks. Other models exist that do predict energy consumption for individual properties, but these tend to provide only monthly or annual average data, which again is of limited value in modelling secondary-distribution networks. To address this, the authors are currently developing load and generation models that will provide data for individual properties at one-minute intervals [1]. This will fully represent the highly stochastic nature of individual customer loads and will be used as input to the network power-flow analysis software being developed in parallel, and discussed in remainder of this paper.

Computer modelling of power flows in high-voltage transmission networks is long-established, typically using Newton-Raphson or Gauss-Seidel iterative methods or embellished versions of these. Balanced 3-phase operation is often assumed, though many commercial software packages can now perform unbalanced analysis, if the necessary additional data is available. Such software has also been extensively used to model primary-distribution networks, though the Newton-Raphson algorithm can sometimes fail to converge, due to high R upon X ratios. Alternative algorithms, exploiting the radial nature of distribution networks, have been developed by Kersting [2] and Shirmohammadi [3] over the last decade. This approach, known by Kersting as the Ladder Iterative Technique, involves making forward and backward sweeps through the network, and avoids the need to construct and manipulate a large network-admittance matrix. It has good convergence characteristics, can include detailed non-linear models of tap-changing transformers etc. and is highly efficient for networks with large numbers of nodes.

Any of the power-flow analysis algorithms mentioned above can be applied to secondary-distribution networks; however, the highly stochastic nature of individual loads renders any single-point-in-time "snapshot" analysis of very limited value. Traditionally, the stochastic nature of individual loads is accommodated by use of Diversity Factors [4]. Ideally, diversity factors should be determined though a comprehensive survey of local loads. In practice however, it is usual to rely on decades of experience with similar loads, which is valid, provided that the loads can be expected to have similar behaviour in the future. This however may not be the case, if there is significant uptake of solar-energy technologies or DCHP or both.

2. POWER-FLOW ALGORITHM

Monte-Carlo versus Probabilistic

In a Monte-Carlo simulation, a single-point-in-time power-flow algorithm is run repeatedly with loads sampled from appropriate probability distributions. If a large number of time-series values are available, the approach can be reduced to simply undertaking a steady state load flow for the data corresponding to each time step. A more elegant, probabilistic, approach manipulates the probability density functions directly as part of the power-flow solution algorithm. Earlier research at CREST [5] [6], implemented two alternative probabilistic power-flow algorithms. This work demonstrated the difficulties of probabilistic power-flow, particularly regarding the handling of partial correlations. Also, because the fast Fourier transforms employed to manipulate the probability density functions are computationally intensive, the work failed to demonstrate any significant reduction in overall computing time, when compared with the Monte-Carlo approach. Consequently the latter approach has been adopted for the project in hand.

Newton-Raphson versus Ladder-Iterative Technique

With Monte-Carlo simulation, the single-point-in-time power-flow algorithm is run a great many times and must therefore be very fast in itself. The authors wrote single-phase (balanced) versions of both Newton-Raphson and Ladder-Iterative algorithms in MATLAB. Both were carefully written, with regard to execution time, and made full use of MATLAB's powerful matrix-manipulation functions. The two programs were tested on a typical radial rural 11-kV primary-distribution network with 328 nodes. They both converged within 5 iterations. The Newton-Raphson algorithm took just over 5 seconds, whereas, the Ladder-Iterative algorithm took under 0.5 seconds. This tends to confirm the findings of other researchers [3], although it should be noted that comparisons of this kind are very sensitive to the chosen test network and unintentional differences in programming efficiency. The Ladder-Iterative algorithm was selected for use in this project.

Unbalanced Power-flow

At the primary-distribution level, it is sometimes reasonable to assume balanced operation and to conduct power-flow analysis on that basis. (Often, the assumption is not entirely sound, but is made anyway because individual phase data is not available.) At the secondary-distribution level, balanced operation cannot normally be assumed and unbalanced analysis is a necessity.

The extension of the balanced Ladder-Iterative program, described above, to perform unbalanced 3-phase power-flow was fairly straightforward: – because well-structured MATLAB code uses matrixes in preference to "for" loops, the extra dimension is readily accommodated. The program was checked against a leading commercial distribution-network analysis package and the results were virtually identical.

The greatest challenge lay in obtaining the cable impedance parameters relevant to unbalanced operation. Some cable manufactures list sequence impedances for high-voltage cables but no such values are readily available for 600/1000-Volt cables. Clearly, unbalanced analysis of low-voltage networks is rarely attempted.

3. TEST NETWORK

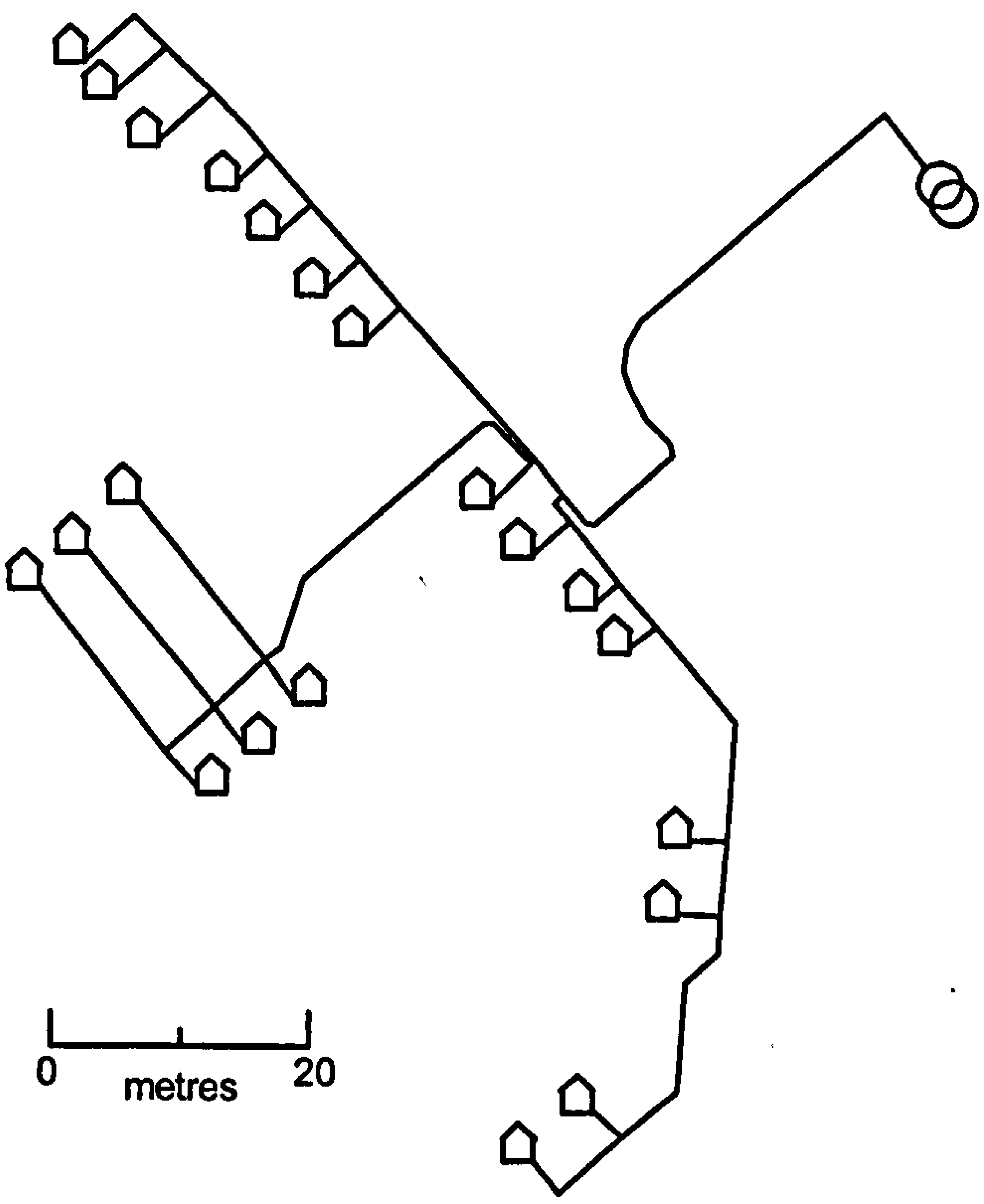

Figure 1 – Test Network

Testing of the software was carried out on a 400/230-Volt secondary-distribution circuit in city-centre Leicester, Midlands, UK. The circuit has 40 nodes and feeds 21 houses, as shown in Figure 1. The locations and cable types of the 3-phase mains were accurately modelled, according to the network operators' database. The locations and cable types of the single-phase services to individual houses were assumed and the choice of phase randomly generated.

The source voltage, at the secondary of the distribution transformer, was taken as 400 V exactly. Clearly this will vary in practice, and it would be very much better to model the whole primary-distribution feeder and all its secondary-distribution circuits, which is the intention in due course.

4. LOAD DATA

The detailed load models, mentioned in the introduction, are not yet complete and so measured load data from 15 houses elsewhere in the Midlands, UK, was employed for demonstration purposes. (Data from all 15 houses recorded on Wed 14-Dec-0095 was used, together with data from 6 of the same houses recorded on Wed 15-Dec-0094.) The data was recoded at 1-minute intervals and displays the highly stochastic nature expected of individual house loads.

It is common to describe loads as constant-power, constant-current, constant impedance or any combination of these, and this can readily be accommodated in the power-flow analysis program. For measured power data, as in this case, the constant-power model is appropriate and was employed.

Reactive power had not been measured so a power factor of between 0.94 and 0.98 was randomly assigned for every data point. This caused the reactive power data to be even more stochastic than the active power. For comparison, a constant power factor of 0.96 was used, and made virtually no difference to the overall results. The load models, mentioned in the introduction, will include estimation of reactive power based on end-use.

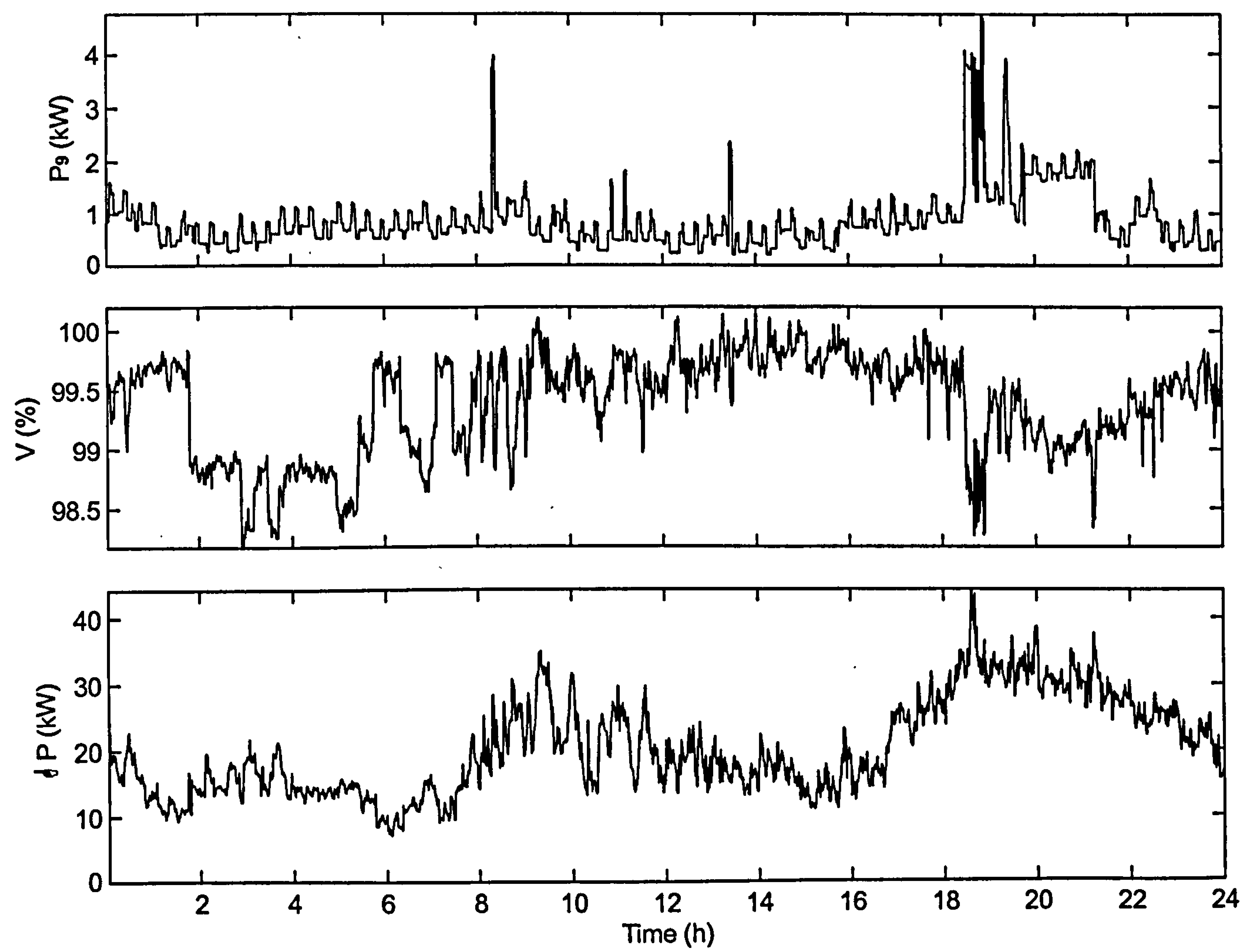

Figure 2 – Example power-flow analysis results

5. RESULTS

One full day's operation of the test network was simulated at 1-minute intervals. This is 1440 time steps and, at each time step, the software calculates 3-phase complex voltages and currents throughout the 40-node network. The whole analysis takes around 100 seconds to perform, which is very respectable at this early stage of development. The program is currently written in MATLAB that is interpreted at runtime. There are various routes through which performance could be dramatically improved.

Some example results are shown in Figure 2. The top graph shows the active power consumed by one of the houses with respect to time throughout the 24-hour day (input data). The highly stochastic nature of an individual customer load is immediately apparent. The middle graph shows the percentage voltage at the same house calculated by the power-flow software. (Recall that this demonstration assumes 100% voltage at the source node. When the rest of the network is considered voltage variations will be much greater.) The bottom graph shows the aggregated load of all 21 houses. The "smoothing" of the load profile through aggregation is apparent.

Retuning to the middle graph (calculated voltage), it can be seen, as expected, that the voltage is depressed around 19:00h when the house load is high. However, the voltage is also depressed during the night; this is due to a neighbour's off-peak heating system and could not have been anticipated from house's own load profile or from the aggregated load profile. Close inspection of the middle graph reveals that the voltage occasionally exceeds 100%. This is due to neutral voltage displacement, and is to be expected in unbalanced 3-phase systems. These points demonstrate that voltage prediction in such networks is not entirely intuitive.

Similar graphs for all the other houses can readily be plotted and examined; likewise conductor currents, losses etc. can be studied. The network area can be increased to include many more houses and the time frame may be extended. Clearly, manual interpretation of the results will quickly become impossible. To address this, post-processing will be provided to identify, for example: frequency of voltage excursions.

6. CONCLUSIONS

Improved power-flow analysis techniques are required for secondary distribution networks, in particular to predict effects caused by significant uptake of solar-energy technologies or DCHP or both. The authors are currently developing such techniques and this paper has discussed the selection of the power-flow analysis algorithm: Monte-Carlo application of an Unbalanced Ladder-Iterative Technique. Initial results are promising and the work is ongoing.

7. ACKNOWLEDGEMENT

This research is funded by the Engineering and Physical Sciences Research Council, UK, project number GR/N35694/01.

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ENERGY and BUILDINGS

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A simple model of domestic lighting demand

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Received 17 July 2003; received in revised form 23 September 2003; accepted 10 October 2003

Abstract

This paper presents a new model of domestic lighting demand. The model is based on half-hourly data measured for a sample of 100 UK homes. It represents one sub-model in an end-user based distributed load model that is being developed to support investigations into the effects on low voltage urban electricity networks of future wide-scale uptake of solar technologies. To capture these effects and to serve applications involving renewable energy technologies (RETs) generally, the model is capable of representing load variations on very fine time-scales, down to 1 min intervals. Additionally, scaling factors are provided to enable prediction of long-term trends and to model some of the most important elements of diversity between connection points that are likely to impact on network performance and design below the 11 kV substation level.

Keywords: Domestic lighting; Demand modelling; Electrical loads

1. Introduction

Demand for lighting represents nearly a fifth of the total electricity consumption in the average home [1]. Whilst the UK Government's white paper on energy [2] expresses an ambition to reduce overall demand, the energy used for lighting is expected to continue on an upward trend [1,3]. Although building related demand, for space and water heating, has received much attention in terms of legislated reduction (e.g. funded insulation improvements or increased boiler efficiency for existing buildings; tightened planning requirements for new developments), lighting and appliance demand is much more complicated and thus difficult to influence. In particular, lighting demand arises from a combination of effects that include the availability of natural lighting and characteristics of the occupants.

The ability to predict the electrical demands of an individual consumer takes on a greater importance as the uptake of renewable energy technologies (RETs) grows. This already presents an issue in sizing systems for remote dwellings that are off-grid, where it is necessary to have an accurate picture not only of the average and peak demands but also variations in demand and supply throughout the year. In urban environments, an appreciation of the pattern of demand can also be important if RETs are densely applied. An understanding of such patterns is also valuable for estimating the associated release of greenhouse gases and for formulating demand reduction strategies at individual, local and national levels. Researchers in this field are hampered by the limited availability of measured data for total and end-use demands, which are costly and time consuming to collect [3,4]. Consequently, there is a need for simulated demand data for input to a variety of energy models.

Since deregulation of the electricity industry in the UK, trading has been based on forward predictions of demand averaged over each half-hour. The use of typical daily profiles for different seasons, days of the week and categories of dwelling (usually related to the supply tariff and fuel used for heating) has become more widespread and the contribution of lighting to the total demand better understood. In the average home on a typical weekday, two peaks occur in the lighting demand, corresponding with morning and evening activities (Fig. 1). The interaction of the availability of daylight and the behaviour of the occupants makes the daily lighting profile difficult to model, as there is no simple linear relationship between demand and time of day.

Libraries of typical half-hourly demand profiles have proved adequate for electricity trading purposes and for the operation and design of distribution networks, especially at the mid to high voltages. For large groups of dwellings, the spikiness of the demand is smoothed due to diversity

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0378-7788/$ – see front matter
doi:10.1016/j.enbuild.2003.10.007

Nomenclature

$D_{lighting}$	lighting demand for given half-hour (normalised, average)
$k_{lighting}$	sine function constant
$L_{lighting\_min}$	minimum value
$L_{lighting\_max}$	maximum value
$L_{lighting\_sine}$	sinusoidal component
N_d	day number (i.e. 1 January = 1)
N_y	number of days in the year
$S_{lighting\_sine}$	sine scale variable

Greek letter

$\phi_{lighting\_sine}$	sine phase variable

between consumers and is consequently easier to predict. As interest in embedded generation from RETs gathers pace, it becomes more important to be able to represent the demands of small groups or even individual consumers. A realistic representation of the diversity of demand between consumers in a group of dwellings is also necessary.

As part of a wider project to investigate the impact of solar technologies on the low voltage electricity networks in cities [5], electrical demand patterns have been modelled at the level of an individual consumer in order to provide a realistic distribution of load. This stochastic model incorporates random elements that represent the diversity between consumers, in terms of appliance ownership and the scale of their demand. Random variations in demand that arise from weather patterns and occupant behaviour are also included. The model covers both domestic and non-domestic consumers and has an end-use basis in order to represent all components of the demand (the model output is used in a performance analysis of the low-voltage network [6]). This paper describes the domestic lighting component of that model, which initially provides a simplified basis for representing the patterns of half-hourly lighting demand when averaged over a group of dwellings. Adjustments to this average case, using some of the parameters that affect lighting demand, allow users to adapt the basic pattern for more specific circumstances of occupancy and to represent some of the elements of diversity.

2. Model description

2.1. Representations of demand data

Modelling either total or component electrical demand is a difficult problem that requires a compromise between accuracy of representation and the computational overheads of storing and processing the underlying model. The problem has been addressed in a variety of ways.

Time series analysis is commonly used for short-term demand forecasting by the electricity industry, using past measurements to determine trends and to predict future values. This method was adopted to provide simulated demand data in a study to size wind generators in remote communities [4]. For reliable accuracy, time series methods often require

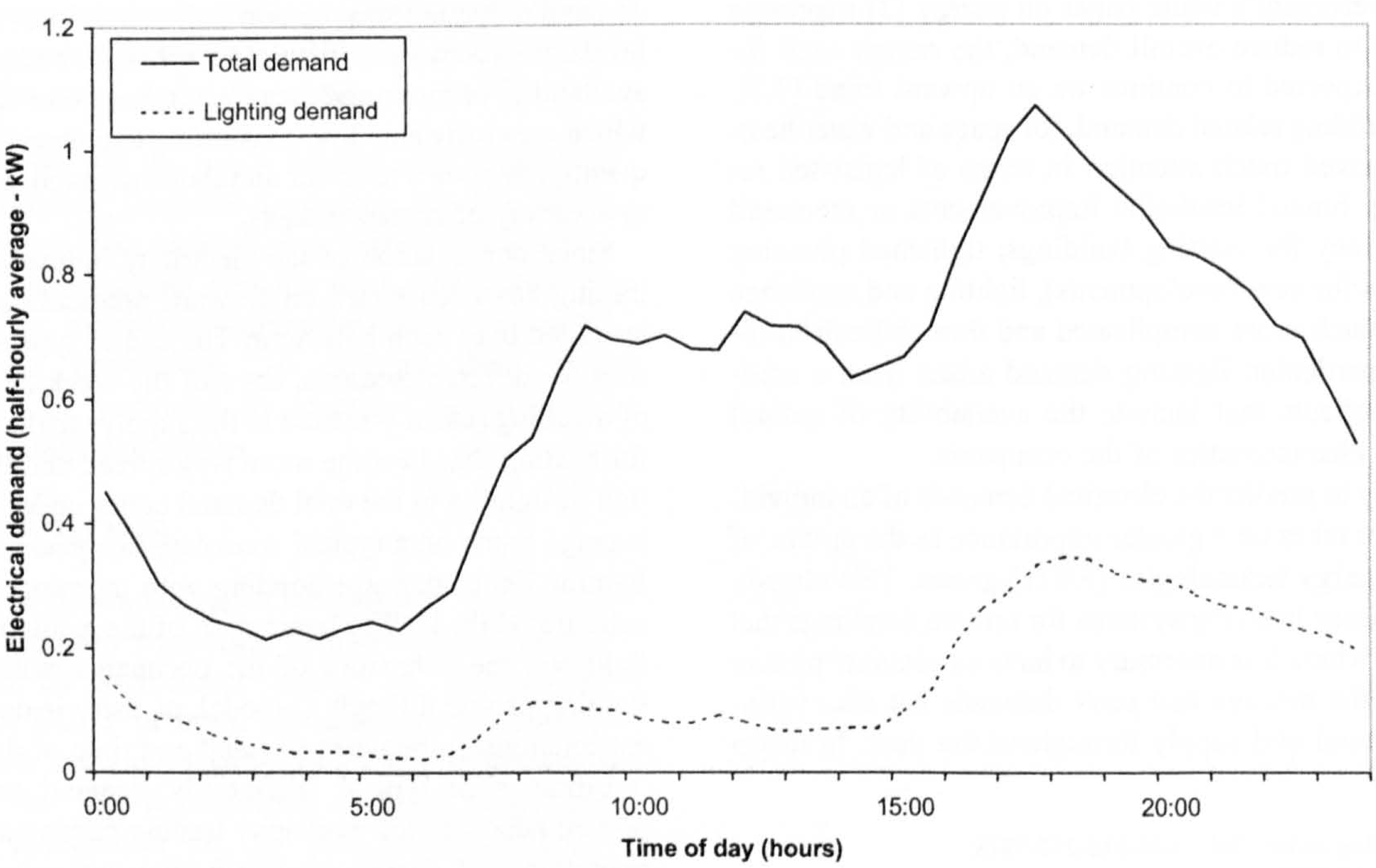

Fig. 1. Contribution of lighting demand to the total electricity demand (averaged over 100 homes) on a typical winter's day—showing total (solid line) and lighting demand (dashed line).

a large number of parameters (over 300 in the previously mentioned example to generate 5 min demands, excluding heating and cooking, over 20 days) although for more constant demands, such as the lighting of offices during working hours [7] as few as 144 terms are required to describe monthly maxima and minima. These models provide good representations of demand and, although aimed at individual consumers, they do include a representation of diversity.

Similarly, Fourier transforms can be used to represent the daily profiles as a series of sinusoidal components. A stochastic model using Fourier transforms was adopted to generate total load data and to represent diversity between consumers for network analysis in New Zealand [8]. In this example, nine separate terms of a Fourier transform are used to represent consumer diversity and 48 to represent the day-to-day variations in the load profile per household. Both time series and Fourier analysis techniques generally provide 'black-box' solutions in which the user cannot easily identify a relationship between the parameters and real-life factors.

Lighting demand was analysed as part of research to assess the benefits of a variety of energy reduction policies [9]. This proposed that daily lighting demand profiles fall into four discrete periods during which occupant behaviour and daylight availability remain relatively similar for each half-hour—night-time, morning peak, daytime and evening peak (Fig. 2). By assuming an underlying function for each period, annual trends may be stored for the parameters that describe each of these functions. The morning peak, for example, was described by a Gaussian function in terms of peak height, width and peak time. The evening peak was described by a more intricate function, which included the description of leading and falling edges. Further relationships were investigated to describe the annual trends for each of these parameters. For example, the leading edge parameter for the evening lighting peak was found to be a sine wave whilst the trailing edge parameter was constant throughout the year. Unlike the time series or Fourier analyses, it may be possible to attribute some real meaning to these trends.

It is especially difficult to model the daily profile of lighting demands since the behaviour of occupants varies greatly during the day and therefore has a large influence (hence morning and evening peaks). Occupant behaviour tends to follow more regular patterns on a day-to-day basis (since people generally get up or go to bed at similar times each day) especially if profiles are generated for different day types. Annual profiles for the demand in a given half-hour tend therefore to have a stronger association with the solar cycle, such as sunrise/sunset times or changes in external ambient temperatures, which have relationships with time that are easier to define.

Some models attempt to describe the effects of the solar cycle and the behaviour of occupants by using separate elements [10,11]. For example, in one such model [10], an availability function determines when the home is likely to be occupied, a proclivity function represents the tendency for particular appliances to be used when the home is occupied and end-use models define the levels of demand when a requirement exists. The latter are generally related to specific data for individual homes, such as the number of occupants or floor area. Since models such as these are entirely related to real features of the demand, they can be very useful

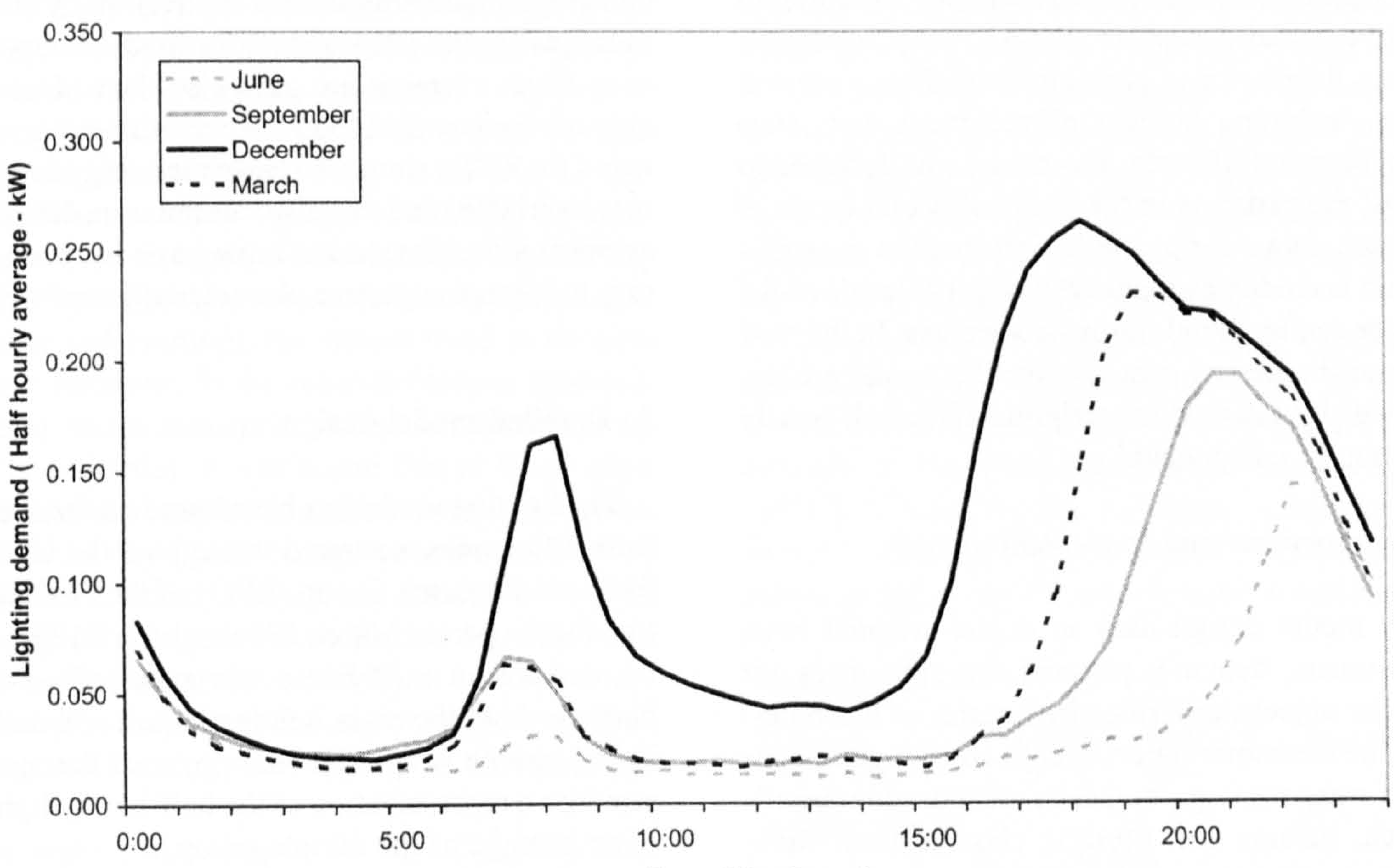

Fig. 2. Daily lighting profile (monthly averages, weekdays) at different times of the year (averaged over 100 homes)—showing demand in June (grey, dashed line), September (grey, solid line), December (black, solid line) and March (black, dashed line).

for exploring different scenarios for energy use or savings. However, they rely on the availability of social data that describe the behaviour of people in their homes, which are as difficult to obtain as the actual demand data.

In order to represent a distributed load on the low voltage network, it is necessary to describe demand at the level of an individual connection point. All of the models just described could achieve this requirement, given sufficient data. To fully describe the load in electrical terms, it is also necessary to represent the demand with regard to the appliances that create the load. The last two techniques described adopt the necessary end-use approach. To allow the model to be used for a variety of energy related studies, a clear, realistic basis is desirable. The models that incorporate end-use demand and occupant behaviour [10,11] are ideal in this respect, provided behavioural data are available. To build an aggregated view of the demand for comparison with measured data at a higher voltage point in the network, the representation of diversity between connection points is also a necessity. The New Zealand study [8] of total domestic demands did achieve this. Finally, to mirror the fluctuations in supply from RETs, it is necessary to describe the demand on a very fine time-scale. Many of the techniques described earlier could achieve this but only if fine-grained demand data are available. No existing models were found that provided all of the desired features and were suitable for deriving 1 min averaged, end-use demand data for individual consumers, with a description of diversity, based on half-hourly data, averaged for a sample group (which were the only data available for this study). Consequently, a new approach was investigated.

The demand model adopted uses annual rather than daily profiles to minimise the difficulties associated with modelling the occupant related aspects of demand. To represent the diversity of demand that exists within a group, a stochastic method was developed to account for various occupant characteristics, including number of occupants, appliance ownership, income and lifestyle. The model was designed to take account of the variation in the availability and levels of accuracy of such data—for example, information on appliance ownership is readily available at a national level, whilst lifestyle indices can be found for postcode areas. In the next section some of the design concepts for the model are described, followed by a detailed description of the half-hourly and sub-half-hourly components.

2.2. Model requirements and conceptual design

The overall model design uses an object-oriented basis in which consumers, demands patterns and appliances are considered to be objects, described by a series of attributes. For example, the consumer object is defined by a geographical location, a category (e.g. 'domestic' or 'non-domestic'), total floor area, income and lifestyle classification. Relationships between the objects describe the way in which consumers and their electrical demands or demands and appliances are associated. A modular, object-oriented approach makes programming the model easier and allows users to make adjustments to represent unforeseen changes in future demand (for example, new appliance demands or attributes can be introduced).

Since the collection of data that is specific to individual households can be expensive in time and money, the new model is designed to operate using different levels of grouping (such as national, regional, local or individual). National data are generally adopted as a default but users can choose to operate the model with more accurate data if available. The use of layers in the model allows the user to apply a series of scaling factors, which can account for a variety of influences, including long term trends in demand, occupant related characteristics and lifestyle patterns. The model stores the annual trends in half-hourly demand, averaged over a group of homes, at the top layer, with the half-hourly and 1 min demands for a specific consumer as outputs of further layers (Fig. 3). The model is sufficiently flexible to accept additional layers or layer elements that adjust annual or daily trends as required—for example, parts of the daily or annual demand could be reduced or eliminated during certain periods, such as vacations in a university hall of residence. (In fact, this feature is used within the wider project to apply the domestic annual demand trends, adjusted by scaling factors for each half-hour, to create a different daily profile for non-domestic consumers, with increased levels of demand during hours when business activity is high.)

Finally the lighting model, as part of the more generalised load model, representing the distribution of demand on the network, is required to output demands averaged over time periods upwards of 1 min, as selected by the user. Different time intervals are used for demand description, depending on national standards and the application. Whilst half-hourly averages are the UK standard for load description, fifteen or even 5 min averages are used elsewhere. One-minute averages are frequently adopted when examining supply and demand for RETs, simply because the energy source is so much more variable, and are also common in demand-side management strategies since a 1 min basis has been found necessary to capture appliance characteristics more precisely [12].

3. Detailed model design

The lighting model has been based on the averaged results from 100 homes, scattered throughout the UK, provided by the Load Research Group (LRG) of the Electricity Association for the period March 1996 and April 1997. In this study, the demand in each home was averaged on a half-hourly basis for both the main lighting circuit and the more significant portable lamps. The first layer of the model therefore provides a representation of the half-hourly lighting demand as an average of the sample group.

Analysis of the data suggests that annual trends have a clearer relationship to the solar cycle than the daily trends. The annual trends generally have a sinusoidal basis with

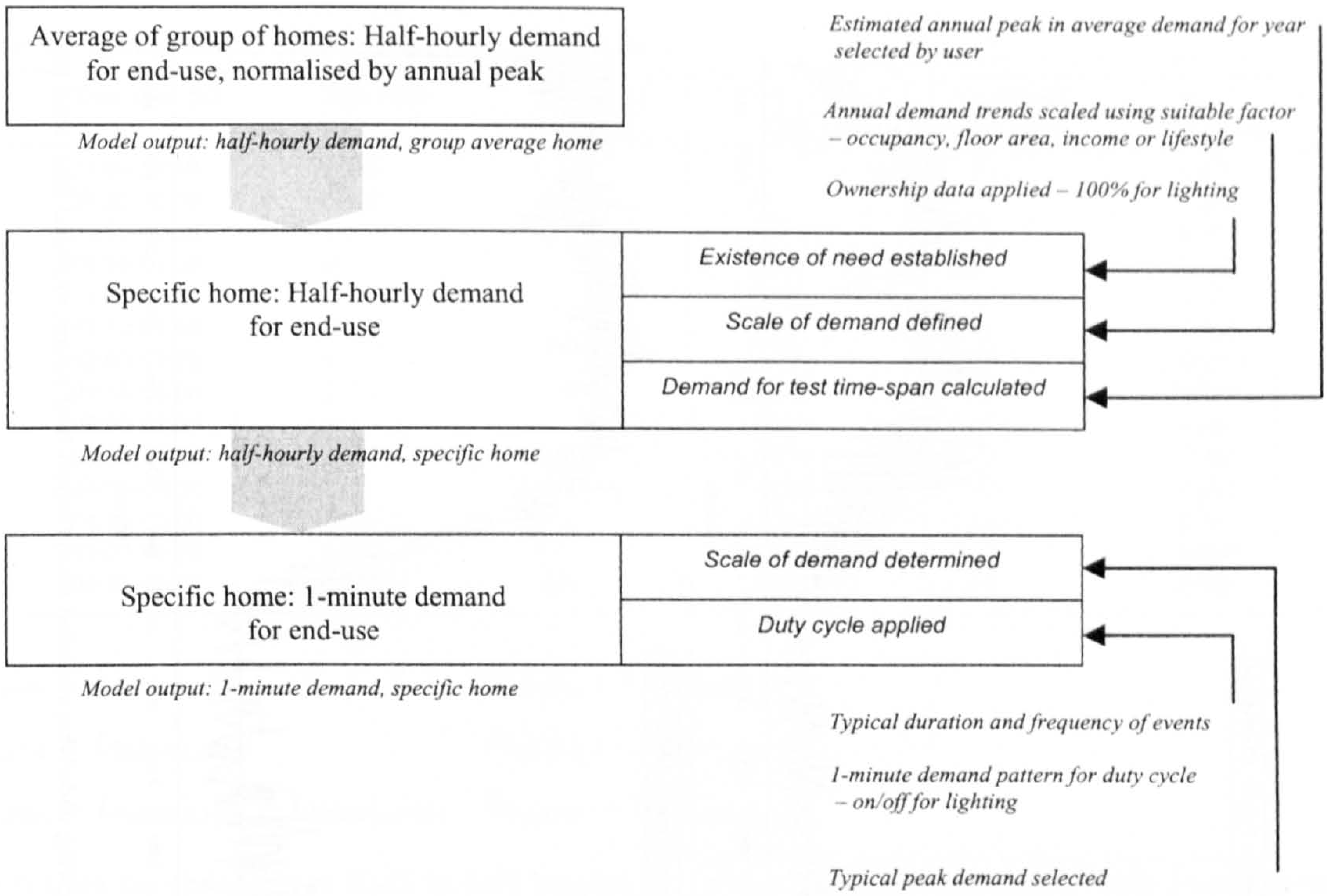

Fig. 3. Schematic diagram illustrating concept of the load models.

respect to day number (1 January = 1) due to the variation in the timing of sunrise and sunset as well as the effects of annual weather patterns. Basing the model on these annual trends avoids the need to make distinctions in the way that the demand is modelled at different times of the day—the annual trend of each half-hour is modelled in a similar way. Analysis of the LRG data revealed that the annual trends could be represented by four key elements—minimum and maximum demand levels and two sinusoidal components. The trends in each half-hour include different contributions from each of these elements, depending on the time of day.

For those half-hours when daylight availability changes through the year (for example, 07:00–07:30 h, Fig. 4b and 19:30–20:00 h, Fig. 4d), due to variations in sunrise and sunset (i.e. morning and evening), the annual trend in demand tends to fall to a minimum in the summer (natural light normally available) and a maximum in the winter (when no natural light is available). It was found that at other times of the year, the demand can be described by two sinusoidal elements with a 34 day phase change between 02:00 h on the last Sunday of October and the last Sunday of March, the timing for clock change between British Summer Time (BST) and Greenwich Mean Time (GMT). A leading or lagging phase change (to represent the step changes in demand in the morning and evening) was applied to the sinusoidal components.

During the night (for example, 04:30–5:00 h, Fig. 4a), when there is no natural lighting available, it was found that the demand is virtually constant with no minimum or maximum demand level and could be described simply by small amplitude sinusoidal components, probably indicating a slight annual trend in occupant behaviour (that broadly follows the inverse of patterns in external ambient temperature) during the night.

During the day (for example, 12:00–12:30 h, Fig. 4c), when natural light should be available (except in extreme weather conditions), there were no maximum levels of demand. The annual trend in lighting demand was fairly flat, at a minimum level, during much of the year but required the two sinusoidal components to model a peak in demand between September and March. Again, these effects may be due to the changes in ambient temperature affecting occupant behaviour as well as annual patterns of weather affecting cloud cover and light availability.

The values for the required parameters and use of minima and maxima were determined, for each of the half-hours, as part of a fitting routine, which minimised the difference between the measured data and the model output, using the method of least squares (weekday values are provided in Tables 1–4). Therefore, the annual trend (normalised by the annual peak) in half-hourly demand is represented by

$$L_{\text{lighting\_sine1}} = S_{\text{lighting\_sine1}} \sin\left\{2\pi\left(\frac{(N_{\text{d}}+n)}{N_{\text{y}}}\right) - \phi_{\text{lighting\_sine1}}\right\}$$

$$L_{\text{lighting\_sine2}} = S_{\text{lighting\_sine2}} \sin\left\{2\pi\left(\frac{(N_{\text{d}}-n)}{N_{\text{y}}}\right) - \phi_{\text{lighting\_sine2}}\right\}$$

$$L_{\text{lighting\_sine}} = L_{\text{lighting\_sine1}} + L_{\text{lighting\_sine2}} + k_{\text{lighting}}$$

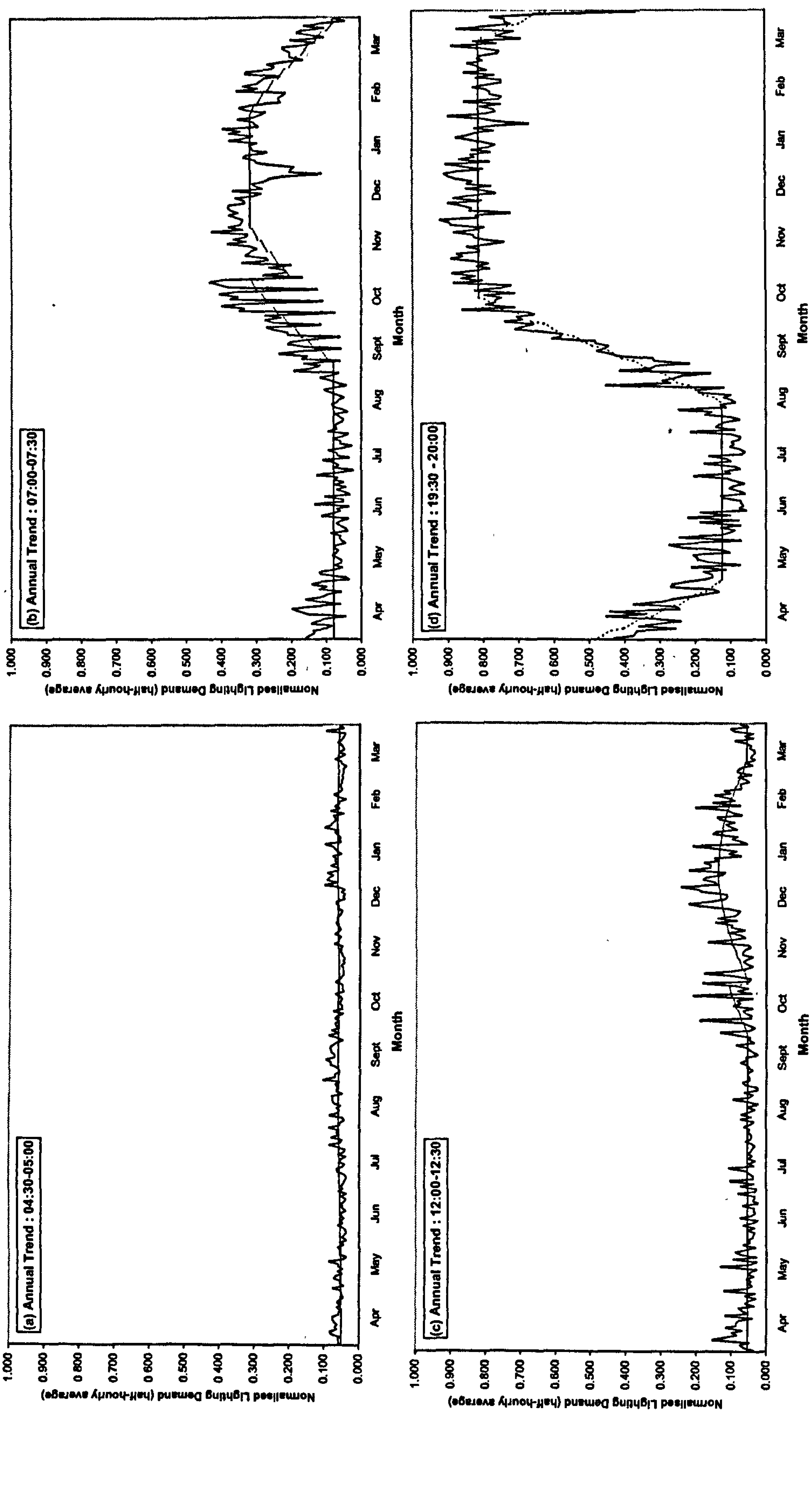

Fig. 4. Annual trends in half-hourly averaged lighting demand for four different times of the day (weekdays)—showing underlying modelled trend (dashed line) against measured data (solid line).

Table 1
Half-hourly averaged lighting demand: parameter values for 23:00–06:00 h

Half-hour reference	Time span (h)	Sine scale variable 1	Sine phase variable1	Sine scale variable 2	Sine phase variable 2	Sine constant	Sine S.D.
47	23:00–23:30	0.049	5.3	0	–	0.472	0.047
48	23:30–00:00	0.035	5.3	0	–	0.366	0.048
1	00:00–00:30	0	–	0.011	5.8	0.263	0.049
2	00:30–01:00	0	–	0.004	5.9	0.186	0.040
3	01:00–01:30	0	–	0.003	4.3	0.140	0.035
4	01:30–02:00	0	–	0.006	3.7	0.110	0.026
5	02:00–02:30	0	–	0.008	3.9	0.092	0.022
6	02:30–03:00	0	–	0.009	4.0	0.079	0.018
7	03:00–03:30	0	–	0.006	3.8	0.069	0.016
8	03:30–04:00	0	–	0.005	3.9	0.065	0.014
9	04:00–04:30	0	–	0.005	3.9	0.062	0.014
10	04:30–05:00	0.006	0.9	0.010	3.6	0.057	0.013
11	05:00–05:30	0.005	0.5	0.013	3.5	0.058	0.014
12	05:30–06:00	0.009	4.0	0.007	4.1	0.069	0.014

If $L_{\text{lighting\_sine}} \leq L_{\text{lighting\_min}}$, $\quad D_{\text{lighting}} = L_{\text{lighting\_min}}$

If $L_{\text{lighting\_sine}} \geq L_{\text{lighting\_max}}$, $\quad D_{\text{lighting}} = L_{\text{lighting\_max}}$

If $L_{\text{lighting\_max}} > L_{\text{lighting\_sine}} > L_{\text{lighting\_min}}$, $\quad D_{\text{lighting}} = L_{\text{lighting\_sine}}$

where $n = 0$ from the change from GMT to BST (occurs at 02:00 h on the last Sunday of March) until the change from BST to GMT (occurs at 02:00 h on the last Sunday of October). Otherwise, $n = 34$.

The data for the half-hourly demand show a day-to-day variation from this basic trend, probably arising from variations in the weather and the detailed behaviour of the occupants. Analysis of the error between the measured data and the calculated trends suggests that this variation could be adequately modelled as a normally distributed random component, with zero mean and a value for the standard deviation (that varies with each half-hour) for the sinusoidal component and, where relevant, the minimum and maximum demand. Any calculated negative demands are set to zero. This combination of components provides annual trends that have a good fit with the measured data from the LRG sample (for example, 19:30–20:00 h, Fig. 5).

The annual trend for each half-hour is described by a maximum of ten parameters (minimum level and standard deviation, maximum level and standard deviation, scale and phase for two sinusoidal functions, a constant and standard deviation for the sinusoidal component) although not all are required for every half-hour. Since lighting demand can vary significantly depending on the day of the week (for example, the morning peak demand is much lower and spread over a wider time span on Sundays compared to weekdays due to the greater diversity in the time of waking) it is necessary to use different sets of parameters for weekdays, Saturdays and Sundays. Demand is also very different during public holidays, although these can be associated with either Saturday or Sunday demand. The value sets for the variables to describe each half-hourly relationship are stored in a database such that a complete annual pattern for the half-hourly lighting demand for the average of a group of homes can be generated in seconds.

The model assumes that the underlying pattern of lighting demand remains constant from year to year although allowance is made for the longer-term increasing trend in total annual consumption. The half-hourly model is normalised in terms of the annual peak demand and year-on-year trends in the peak value can be used to adjust the absolute level of demand in kW (Fig. 6).

Demand for the average of a group of homes can be used to predict demand at a national level, but for many purposes, including the representation of the distributed demand in groups of dwellings, it is necessary to adapt the average data to reflect the demand in individual dwellings. Lighting demand is related to the number of rooms and occupants in a

Table 2
Half-hourly lighting demand: parameter values for 06:00–08:00 h

Half-hour reference	Time span (h)	Minimum level		Maximum level		Sine 1		Sine 2		Constant	Sine S.D.
		Value	S.D.	Value	S.D.	Scale	Phase	Scale	Phase		
13	06:00–06:30	–	–	0.091	0.017	0.015	4.2	0.045	4.7	0.111	0.013
14	06:30–07:00	0.051	0.013	0.169	0.035	0.114	4.7	0.030	4.3	0.149	0.026
15	07:00–07:30	0.080	0.025	0.318	0.063	0.035	4.4	0.295	4.2	0.092	0.058
16	07:30–08:00	0.095	0.045	0.452	0.133	0.026	5.8	0.498	4.1	0.008	0.072

Table 3
Half-hourly lighting demand: parameter values for 08:00–17:00 h

Half-hour reference	Time span (h)	Minimum level		Sine 1		Sine 2		Constant	Sine S.D.
		Value	S.D.	Scale	Phase	Scale	Phase		
17	08:00–08:30	0.098	0.139	0.063	4.9	0.453	4.2	−0.028	0.065
18	08:30–09:00	0.077	0.024	0.048	4.6	0.352	4.2	−0.086	0.061
19	09:00–09:30	0.064	0.024	0.021	5.6	0.255	4.1	−0.039	0.062
20	09:30–10:00	0.060	0.027	0.022	5.5	0.206	4.1	−0.027	0.056
21	10:00–10:30	0.057	0.026	0.031	4.6	0.182	4.2	−0.028	0.053
22	10:30–11:00	0.057	0.027	0.018	5.0	0.164	4.1	−0.022	0.049
23	11:00–11:30	0.060	0.029	0.027	4.7	0.153	4.2	−0.025	0.041
24	11:30–12:00	0.057	0.029	0.017	4.7	0.159	4.2	−0.030	0.040
25	12:00–12:30	0.054	0.024	0.009	4.7	0.139	4.2	−0.009	0.042
26	12:30–13:00	0.056	0.030	0.019	5.6	0.145	4.2	−0.023	0.042
27	13:00–13:30	0.059	0.032	0.010	6.1	0.146	4.2	−0.013	0.041
28	13:30–14:00	0.055	0.024	0.013	0.0	0.145	4.1	−0.007	0.047
29	14:00–14:30	0.054	0.031	0.018	5.1	0.147	4.2	−0.016	0.047
30	14:30–15:00	0.054	0.025	0.029	5.8	0.153	4.0	−0.018	0.053
31	15:00–15:30	0.058	0.026	0.054	5.1	0.184	4.1	−0.042	0.064
32	15:30–16:00	0.064	0.031	0.188	4.9	0.269	4.1	−0.141	0.078
33	16:00–16:30	0.073	0.040	0.351	4.9	0.347	4.0	−0.224	0.082
34	16:30–17:00	0.083	0.046	0.607	4.9	0.107	4.4	−0.016	0.069

home as well as their income and lifestyle [13]. These factors, most of which are interrelated, have a far greater effect on the morning and evening peaks, when the demand is sensitive to occupant activity, than at other times of the day. The model adopts scaling factors applied to each of the half-hourly annual trends to adjust the average demand to suit the characteristics of individual consumers, thus adjusting the daily pattern as well as the overall scale of demand. The simplest parameter to select is the number of occupants, which using the standard occupancy from the BREDEM-8 model [14] can be derived from the total floor area (the application in which the model is being used automatically generates floor areas from building outlines, based on aerial maps [15]). A similar scaling adjustment for each half-hourly annual trend is made using the ACORN lifestyle classification, which is readily available for postcode areas [16]. The user may alternatively adopt scaling factors for income (characterised as being ‘above’ or ‘below’ the current national average annual income) in cases where this information is available. This provides a degree of diversity in lighting demand between consumers based on variations of the average demand patterns.

The model does not take account of differing occupancy patterns, such as homes with day-long occupation compared to those that are unoccupied during the day time. Taking account of these patterns would improve the modelling of diversity, particularly during the winter and for mid-day and the early evening. However, such patterns of occupancy are not widely available. In areas where occupancy patterns will clearly affect the demand pattern, for example, in university halls of residence, when flats may be unoccupied during holiday periods, or in clusters of homes for the elderly, when

Table 4
Half-hourly lighting demand: parameter values for 17:00–23:00 h

Half-hour reference	Time span (h)	Minimum level		Maximum level		Sine 1		Sine 2		Constant	Sine S.D.
		Value	S.D.	Value	S.D.	Scale	Phase	Scale	Phase		
35	17:00–17:30	0.087	0.040	0.805	0.060	0.564	4.9	0.157	4.3	0.129	0.085
36	17:30–18:00	0.087	0.038	0.826	0.064	0.560	4.8	0.333	4.5	0.192	0.103
37	18:00–18:30	0.094	0.042	0.847	0.063	0.476	4.7	0.554	4.5	0.247	0.092
38	18:30–19:00	0.115	0.054	0.848	0.060	0.439	4.7	0.728	4.5	0.326	0.079
39	19:00–19:30	0.127	0.069	0.839	0.058	0.370	4.7	0.705	4.5	0.459	0.086
40	19:30–20:00	0.125	0.054	0.813	0.050	0.256	4.7	0.460	4.5	0.581	0.079
41	20:00–20:30	0.149	0.089	0.789	0.053	0.370	4.7	0.322	4.5	0.712	0.055
42	20:30–21:00	–	–	0.782	0.056	0.473	4.7	0.188	4.5	0.823	0.068
43	21:00–21:30	–	–	0.759	0.063	0.390	4.7	0.322	4.7	0.980	0.055
44	21:30–22:00	–	–	0.743	0.044	0.375	4.8	0.012	3.5	0.801	0.057
45	22:00–22:30	–	–	0.706	0.043	0.172	4.8	0	–	0.697	0.042
46	22:30–23:00	–	–	0.623	0.045	0.083	5.2	0	–	0.590	0.042

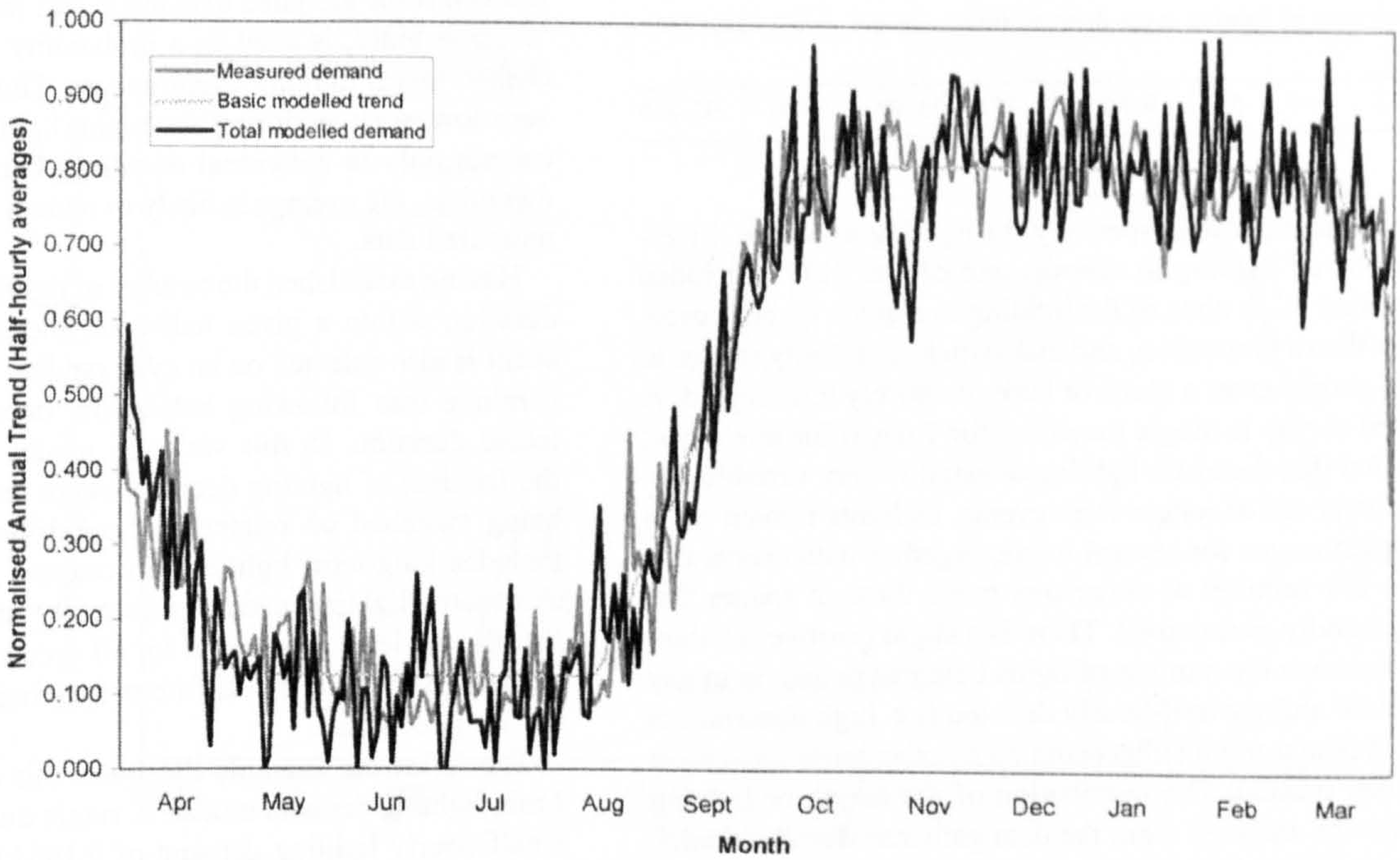

Fig. 5. Basis of the domestic lighting model (half-hourly averaged demand) compared to measured data (averaged over 100 homes)—weekdays, 19:30–20:00 h, showing measured data (grey, solid line), basic trend (grey, dashed line) and total modelled demand (black, solid line).

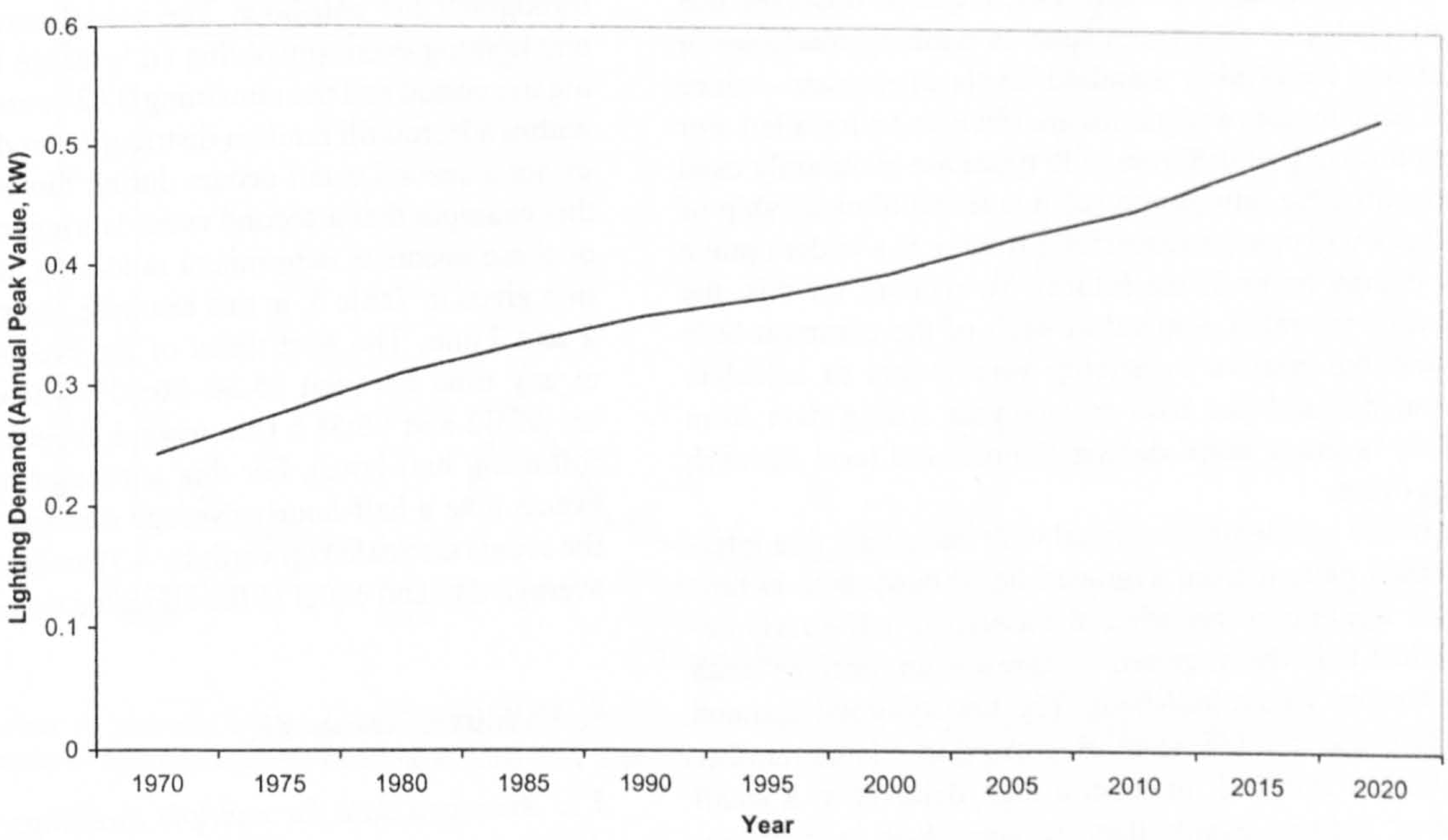

Fig. 6. Estimated trend in annual peak for lighting demand (half-hourly average, based on data from [1]) for group average.

homes may be occupied all day, the user may introduce an additional element as an extra layer in the model. For example, occupancy patterns, that are either daily or annual, may be constructed with a value of either 1 (occupied) or 0 (unoccupied) and used as a gate for the half-hourly demands assigned to the consumer. Alternatively, demand may be scaled upwards during times of the day when there is likely to be more activity than for the average case.

4. Derivation of less than half-hourly demand

Thus far, the model provides an assignment of lighting demand that is specific to an individual consumer. This allocation is for a user-defined time span and provides the half-hourly averaged demand. The next step is to use the assigned demand to calculate a typical minute-by-minute pattern of lighting usage. Very little data are available at the

Table 5
Distribution of lighting event duration (min)—ranges giving equal probability

1	2	3–4	5–8	9–16	17–27	28–49	50–91	92–259

1 min demand level, especially for lighting in homes. Investigations of lighting in schools and offices [17] concluded that either all or none of the lighting in a given space is used, rather than a proportion, and that switching activity relates to when people enter a space or leave it entirely unoccupied. A limited survey (a single dwelling, for 7 days) for this model revealed that domestic lighting demand is very variable, being composed of longer term events, as lights remain on in occupied rooms for several hours, together with events that last a few minutes as occupants move through spaces that are generally unoccupied. There is a slight positive relationship between the number of lights being switched on in any half-hour and the half-hourly demand (i.e. high demand not only indicates more bulbs being on but also more movement between spaces). The distribution of the length of lighting events was analysed from the data gathered. For the model, the time span of an event is approximated by selecting an event length at random, using an equal probability that the duration will lie in each of the ranges given in Table 5.

When considering other end-uses, it can be observed that the duty cycles of appliances such as washing machines or refrigerators have fairly standard levels of demand—since similar sized motors and pumps are likely to be installed. For lighting a variety of different bulb types are commonly used and over time the ratings and relative levels of ownership of these types will change (especially if there is a wider uptake of low energy bulbs in the future). To account for this, the model uses the rated demand of each of the common bulb types and the relative ownership percentages to calculate the mean demand per bulb in any year (using data from [1]). This 'average bulb' defines the demand level for each lighting event.

One of the problems associated with deriving a fine interval demand pattern from averaged half-hourly data is how to trigger lighting events when the assigned half-hourly demand is less than that required to represent an 'average' bulb left on for the whole half-hour. The low assigned demand could arise due to a low level of demand in a large number of the homes sampled, or from a high demand in a small number or lighting events that are very short in duration. Consequently, it was necessary to find a method within the model of triggering lighting events when the assigned demand is low and to introduce an element that allows lighting events to take place in some homes on a random basis. For an individual consumer, the assigned half-hourly demand is divided by the rated demand for the 'average bulb'. Any whole number multiples are taken to imply the number of new lighting events that occur during the half-hour (since there is a positive relationship between the number of lighting events and the assigned demand). The remainder, or the fraction if the assigned demand is less than the rating of the 'average bulb', is used as a probability that represents the chance that a lighting event occurs. Thus when demand is very low, such as during the night, lighting events can occur not only in individual dwellings but within a group of dwellings, the average is likely to remain consistent with the measured data.

Having established the number of lighting events and their duration within a given half-hour, the start time for each event is also selected on an even random basis. Events may continue into following half-hours, depending on the selected duration. In this way, the model is able to capture the features of lighting demand where the number of bulbs being switched on relates to the half-hourly demand and includes long-term lighting in occupied spaces as well as short-term lighting needs in normally unoccupied spaces. Finally, the level of demand for all events in each half-hour is scaled such that the half-hourly average matches that of the assigned value.

The following example illustrates this description of the 1 min lighting demand model. A single dwelling is assigned a half-hourly lighting demand of 0.104 kW between 05:30 and 06:00 h. Currently, an average light bulb has a demand rating of 0.073 kW. The assigned demand is therefore equivalent to 1.42 of these 'average bulbs' being on constantly throughout the half-hour. The model assumes that at least one lighting event (involving an 'average bulb') occurs during the period and the remaining 0.42 is used as a probability within a Bernoulli random distribution to determine whether or not a second event occurs during the period (assume for this example that a second event is triggered). The duration of these events is determined randomly, using the distribution given in Table 5; in this example, the two events last for 2 and 7 min. The start times of the events are set to occur at any time between 05:30–06:00 h—here, the start times are 05:32 and 05:56 h (the second event continues into the following half-hour). For this particular half-hour, the two events give a half-hourly average demand of 0.022 kW and the events are scaled upwards by 4.72 to bring the half-hourly average demand equal to the allocated demand of 0.104 kW.

5. Validity of the model

5.1. Averaged data for multiple dwellings: half-hourly demand

The half-hourly, group average model provides a good fit with the measured data. In terms of the annual aggregated demand for the average home, the model predicts a total weekday consumption of 529 kWh, which is within 0.1% of the measured consumption (based on 1996/1997 demand). The model also provides a good representation of the daily demand patterns when averaged over the seasons (e.g. the averaged winter weekday, with a correlation factor of 0.99, Fig. 7a). For an individual day the model estimate of the

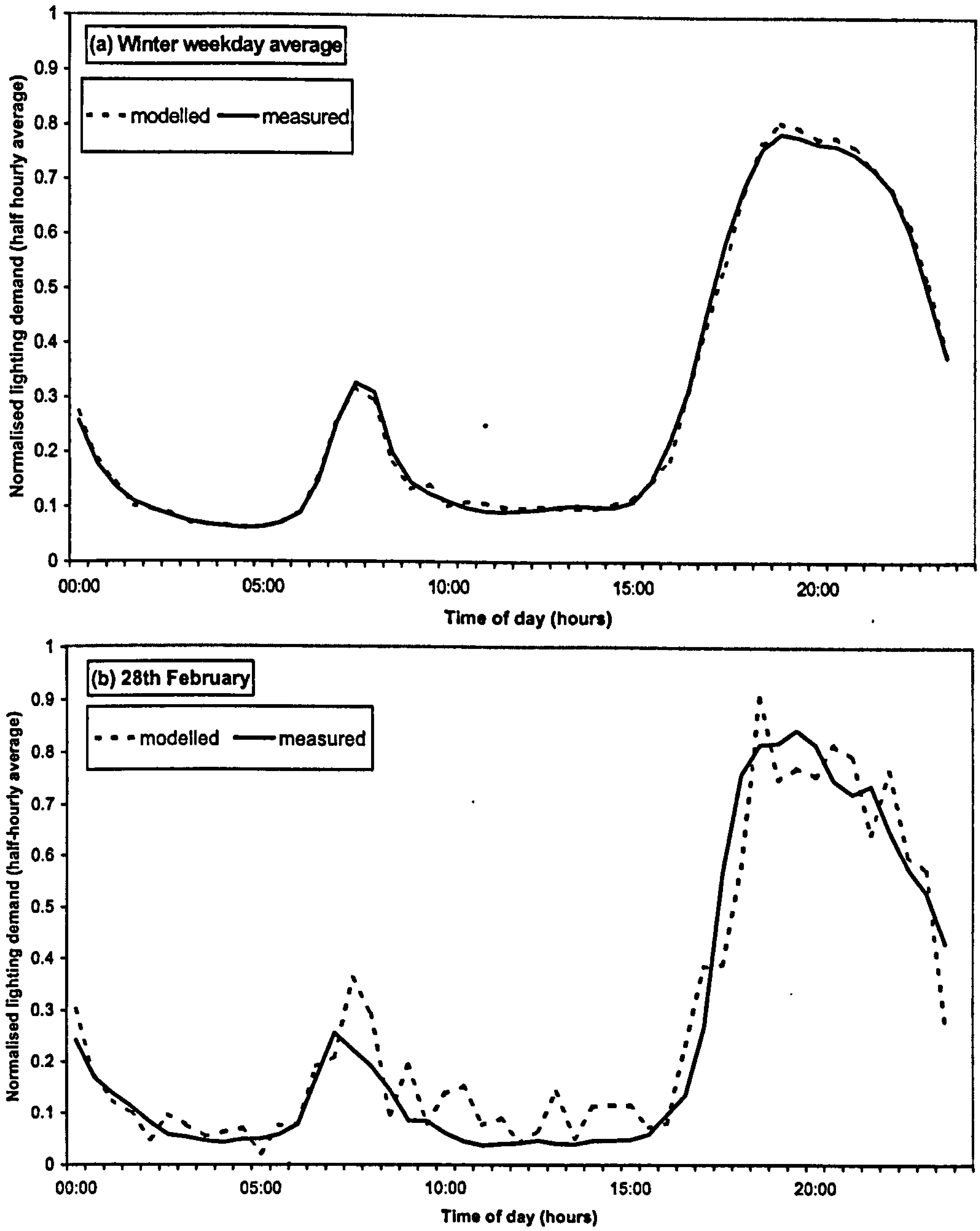

Fig. 7. Comparison of measured and modelled lighting demand (half-hourly average) for (a) the average winter weekday and (b) for a single winter's day (28th February)—showing measured data (black, solid line) against modelled data (black, dashed line).

daily profile shows more variation between half-hours compared to the measured data (e.g. 28th February, with a correlation factor of 0.97, Fig. 7b). This is probably because the model uses an entirely unrelated random element for each half-hour (the random component is added to the annual trend) whereas in reality, the factors, such as cloud cover, that affect lighting demand are less likely to show such a strong variation during a single day. For the purposes of assessing the low voltage performance of the network, the model provides an adequate but worst-case representation of the load. For situations that require a closer representation of the daily profile, smoothing could be applied (for example: exponential smoothing with a damping factor of 0.5–0.6).

5.2. Single dwelling: half-hourly demand

In another survey, lighting demand was measured in a single dwelling (six rooms, four persons, occupied during daytime, above average income) for 7 days and compared with the model output for a single day (taking account of occupancy and income and scaled by an estimated annual peak demand in 2003 of 0.482 kW, based on trends in total lighting

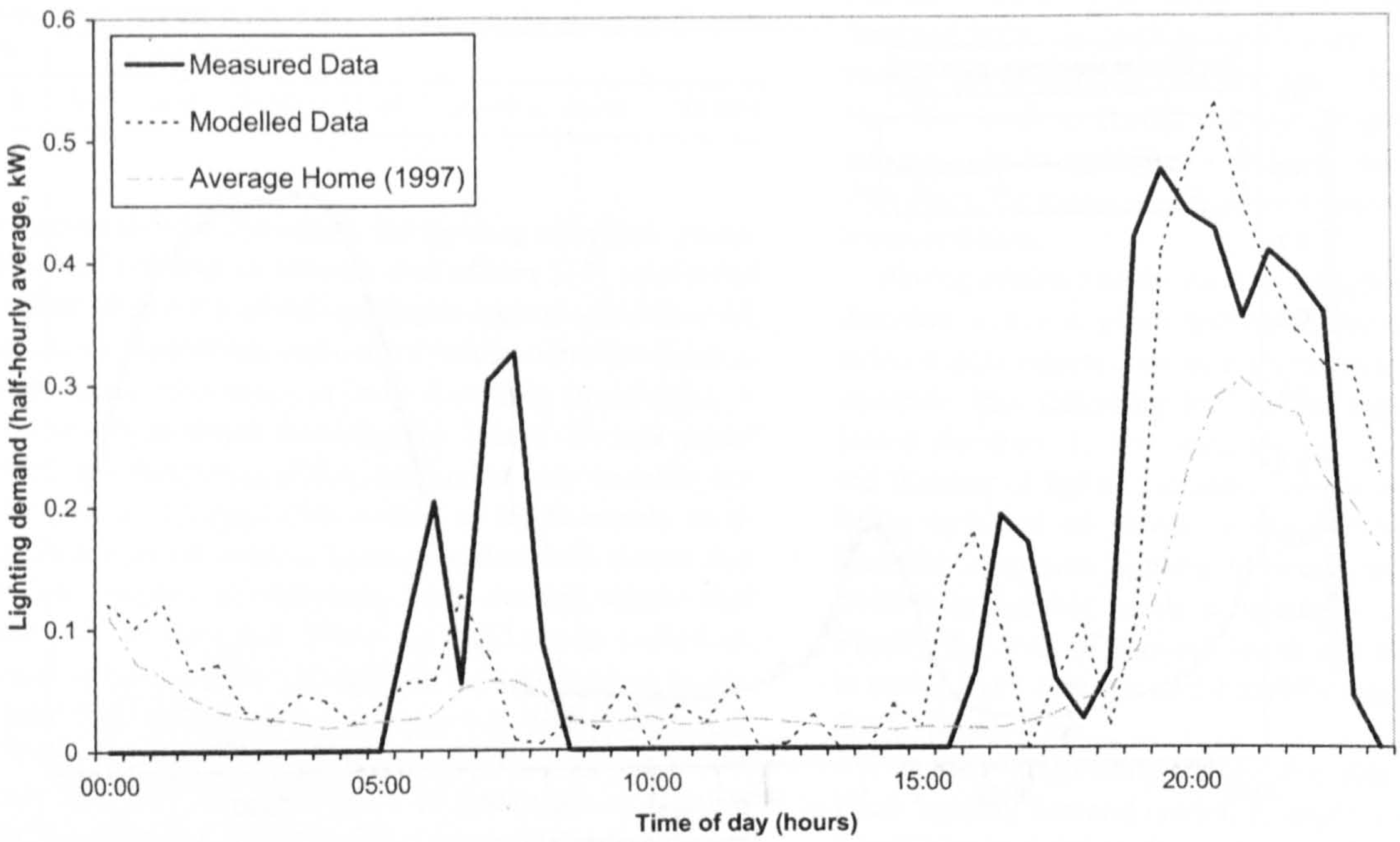

Fig. 8. Comparison of measured and modelled lighting demand (half-hourly average) for a single dwelling (2 April 2003)—showing measured (black, solid line), modelled (black, dotted line) and measured data for the average home (grey, chain-dashed line).

demand from [1]). The results (Fig. 8) illustrate that for this particular home (which has an unusually large kitchen and bathroom), the model underestimates the morning demand but generally captures the evening demand well. The total daily demand in kWh estimated by the model is within 10% of the measured value. The morning demand observed in the test dwelling is much higher when compared against the pattern of demand averaged over the 100 UK homes in the LRG sample of 1997. The demand estimated by the model (which includes specific factors for income and occupancy) is closer to that observed, especially for the evening peak. However, the model would have to be far more detailed in approach to capture all the factors that affect the lighting demand of a specific home, such as the orientation and number

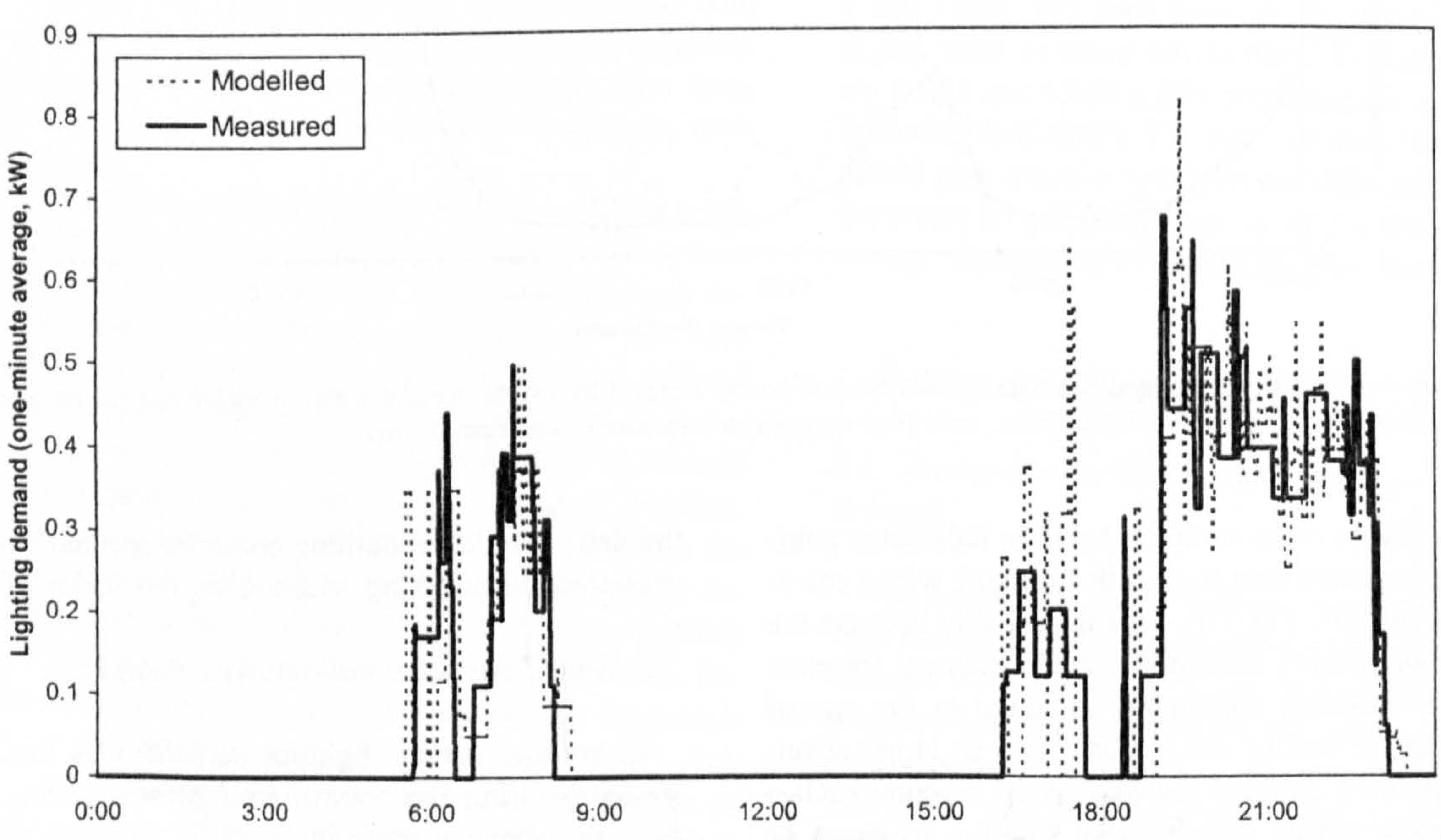

Fig. 9. Comparison of measured and modelled lighting demand (1 min average) for a single dwelling (2 April 2003)—showing measured (solid line) and modelled data (dashed line).

of windows, room sizes and the detailed behaviour of occupants.

5.3. Single dwelling: 1 min demand

Using the measured data at the half-hourly level for the same test dwelling, the minute-by-minute lighting demand was reconstructed, using the sub-half-hourly model. Whilst the model does not attempt to replicate the lighting demand, it is able to capture the broad pattern of combined longer term constant demand with irregular spikes (Fig. 9). The computational demands, in terms of simulation time, of the sub-half-hourly demand model have yet to be established when applied to large groups of homes (which number several thousand on a single feeder from a primary transformer), but use of the model for estimating lighting demands for single homes or small estates or to generate standard demand profiles for random application seems reasonable. Within the wider project, the 1 min lighting demand will be compared against total demand data for 15 homes over a year.

6. Conclusion

The model described gives a useful representation of domestic lighting demand that can provide an indication of energy requirements for an individual home as well as for estimating the aggregated demand or even the distributed loading for groups of dwellings. The facility to work at very fine time-intervals enables the model to capture essential characteristics of domestic lighting demand involving a combination of longer lighting events in normally occupied spaces and shorter lighting requirements in other zones. This represents a significant advance over existing approaches.

The design of the model is also sufficiently flexible to allow the user to track long-term trends in lighting demand and appliance ratings. To represent diversity, the model employs scaling factors that allow for differences in occupancy, income and lifestyle—for which the data can be introduced at any level of accuracy, depending on availability. Whilst the model is not intended to capture all elements of diversity, such as glazing design, room sizes and the detailed behaviour of the occupants, it can be used to provide an indication of demand for a specific dwelling. Unlike many other energy models, the basis of this model can be given a real-life interpretation. The structure of the model, with use of objects and layers, is sufficiently open to allow users to adjust the underlying features to account for special circumstances.

The model will be used as part of a much broader application that will represent the total demand for both domestic and non-domestic consumers to describe the loading on a low-voltage electrical network. The purpose of this study is to provide design and operating support for assessing the effects of large-scale uptake of solar technologies in urban settings. However, the model may have wider applications in matching supply and demand for other RET installations and to examine energy saving policies directed at lighting and appliances.

Acknowledgements

This research is funded by the Engineering and Physical Sciences Research Council, project number GR/N35694/01. The Centre for Renewable Energy Systems Technology, Loughborough University, as a project partner, is developing the network performance tools in which the models described will be applied. The authors are grateful to the Load Research Group of the Electricity Association for providing half-hourly demand data.

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